Application of Crowdsourced Travel Data in Identifying Potential Opportunities for Transportation Demand Management

by

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AUTHOR'S DECLARATION

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

STATEMENT OF CONTRIBUTIONS

I would like to acknowledge the contributions of Dr. Jeffrey M. Casello and Kevin K.L. Yeung to the many ideas that underpin this research, as well as their co-authorship on prior works that have helped to inform this thesis.

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ABSTRACT

Traffic congestion is a major concern that many urban regions contend with. Since the 1970s, transport practitioners have sought out different ways to alleviate the negative impacts of congestion. The concept of Transportation Demand Management (TDM) was born out of this era as a means to address congestion through demand-side approaches that encourage adjustments in travel behaviour. Given its broad mandate, a wide variety of policies and programs fall within the realm of TDM.

To assist in the selection of appropriate TDM strategies prior to implementation, several TDM evaluation models have been developed. However, many analysis techniques require data from past examples of TDM strategy implementation, which are at times difficult to obtain, and would not be available for newly developed and untested policy and program approaches. This thesis builds on the techniques used in past models to present a new model framework that can be used in the identification and evaluation of opportunities to apply TDM strategies. Employing a pivot-point logit model, the model relies only on quantifications of traveller utility through generalized cost calculations. Crowdsourced travel data collected from the Google Maps web-mapping application has been used as the primary source of data behind the generalized costs. The model was applied to a set of test corridors in the Greater Toronto and Hamilton Area (GTHA) which represent major cross regional travel flows. Results of the model were found to be directionally consistent with known conditions of the transportation system in the study area, though adjustments are needed to the model coefficients in order to more accurately reflect the magnitude of behavioural change to be expected from travellers.

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LIST OF ABBREVIATIONS

API	Application Program Interface
AT	Active Transportation
BRT	Bus Rapid Transit
CUTR	Center for Urban Transportation Research
EPA	Environmental Protection Agency
ETR	Express Toll Route
FHWA	Federal Highway Administration
FMS	Future Mobility Survey
GPS	Global Positioning System
GSM	Global System for Mobile Communication
GTFS	General Transit Feed Specification
GTHA	Greater Toronto and Hamilton Area
HITS	Household Interview Travel Survey
HOT	High-Occupancy Tolling
HOV	High-Occupant Vehicle/High-Occupancy Vehicle
IIA	Independence of Irrelevant Alternatives
LRT	Light Rail Transit
RER	Regional Express Rail
SOV	Single Occupancy Vehicle/Single Occupancy Vehicle
TCM	Transportation Control Measure
TDM	Transportation Demand Management
TEEM	TDM Effectiveness Evaluation Model
TMA	Transportation Management Association
TRIMMS	Trips Reduction Impacts of Mobility Management Strategies
TSM	Transportation Systems Management
TTS	Transportation Tomorrow Survey
VOIP	Voice Over Internet Protocol
WTRM	Worksite Trip Reduction Model

LIST OF SYMBOLS

C_{fare}	Fare charge
C_{fuel}	Fuel cost
$C_{parking}$	Parking charge
C_{toll}	Toll charge
GC_{auto}	Generalized cost for auto travel
$GC_{j,t}$	Generalized cost of mode or alternative j at time t
$GC_{transit}$	Generalized cost for transit travel
i	Mode i or alternative i
i(m,s)	Alternative across mode (m) and space (s)
j	Mode j or alternative j
l	Index of all alternatives within the choice set across space, mode, and time
m	modal alternative within choice set
P(i)	Starting share for mode i
P(j)	Starting share for mode j
P'(j)	Adjusted share for mode j as a result of changes in utility or generalized cost
q	Time variance from time of analysis (t)
s	spatial alternative within choice set
t	Time of analysis
t_{access}	Access time
t_{early}	Early arrival time
t_{egress}	Egress time
t_{IV}	In-vehicle travel time
t_{late}	Late arrival time
t_{wait}	Wait time
VOT	Value of Time
β_{access}	Coefficient for access time
β_{early}	Coefficient for early arrival time
β_{egress}	Coefficient for egress time
β_{fare}	Coefficient for fare charge
β_{fuel}	Coefficient for fuel cost
β_{IV}	Coefficient for in-vehicle travel time
β_{late}	Coefficient for late arrival time
$\beta_{parking}$	Coefficient for parking charge
β_{toll}	Coefficient for toll charge
β_{wait}	Coefficient for wait time
ΔU_i	Change in utility of mode i
ΔU_j	Change in utility of mode j

1.0 INTRODUCTION

1.1 RESEARCH MOTIVATION

Congestion is a major concern in many urban areas. On a personal level, traffic delays cause stress and take away valuable time from an individual's day; on a societal level, congestion results in lost productivity for the economy, as well as increased emissions and worsened air quality. In all, time spent in traffic results in a decrease in quality of life.

Heavy reliance on the personal automobile is one of the main contributors to congestion. With many vehicles holding a single-occupant, personal automobiles waste a significant amount of road capacity. While alternatives to the personal automobile exist, these options do not always compete well against the convenience of one's own vehicle. Cities that have been historically designed for the personal automobile inherently elevate it as a more viable option in many different aspects, from the organization of land uses, to the geometry of the road network, and the location and availability of parking. As such, other modes, such as transit, cycling, and walking, have difficulty competing with the level of convenience and flexibility that is offered by the personal automobile.

Since the 1970s, transport practitioners in North America have sought a number of different ways to alleviate congestion brought on by auto-oriented lifestyles. Many of the strategies that have been developed fall within the realm of Transportation Demand Management (TDM)—a term that encapsulates a wide range of policies, programs, and initiatives intended to motivate behavioural changes that help to optimize the use of the transportation system (Meyer, 1999; National Center for Transit Research, 2007; Wachs, 1990). TDM consists of a variety of strategies that encourage travellers to adjust their travel behaviour in space, time, mode, or demand, often taking advantage of underutilized parts of the transportation system (Casello, 2015; Federal Highway Administration, 2012). Central to the concept of TDM is the use of incentives and disincentives to signal to users the need for alternative behaviour. Where alternative travel options are closely comparable, it is regarded that travel behaviours are more responsive to minor adjustments to utility, such as those induced by small incentives and disincentives. For example, an increase in parking charges would only motivate travellers to shift away from travel by private auto if a viable alternative exists. If the alternative, travel by transit, involves a significantly longer travel time, a traveller may rather take on the additional parking charges rather than consider shifting their behaviour. This is consistent with widely understood concept of elasticity of demand, which proposes that changes in the price of a good or service results in a proportional response to the change in demand for the good or service.

Given the wide range of TDM strategies available, selection of appropriate policies, programs, and initiatives to suit the circumstances of a specific analysis area, corridor, or site is an important task. While conventional travel demand models can be used to evaluate the effectiveness of certain TDM interventions, the models also tend to be data-intensive and require highly specialized knowledge and skills to develop and manage. The regional scale at which conventional travel demand models are typically applied also make these evaluation tools less suitable for use in revealing opportunities for TDM at a corridor or area level. Without a mechanism for recognizing opportunities, practitioners are left to rely on anecdotal experience, ad hoc studies on specific strategy applications, or trial and error of different TDM approaches within the transport demand modelling framework.

1.2 RESEARCH OBJECTIVES

The objective of this thesis is to develop and employ an easy-to-apply yet sophisticated set of methods that can be used to identify opportunities where TDM strategies can be applied to regulate travel demands at a corridor level. The sketch model, or analysis framework, has been developed to undertake two main functions. The first is to identify opportunities for TDM within corridors of travel. The second is to estimate the performance of potential TDM strategies applied to the same corridors of travel. The methods used in the model have been selected to be accessible to practitioners with a wide range of knowledge and skills, and utilize data that are relatively easy to acquire as compared to traditional commuter surveys which are commonly required for travel demand modelling.

In parallel to the development of the analysis framework, this thesis aims to explore the usability of emerging data sources such as crowdsourced location data. More specifically, this thesis seeks to explore the applicability of Google Maps travel data in transportation analyses such as TDM evaluations. Using crowdsourced location data collected through a publicly available web-mapping interface, this application of the analysis framework explores the possibility of conducting TDM analysis with easily accessible data and relatively simple analysis techniques that could be executed by practitioners with varying degrees of analysis expertise.

In achieving these objectives, this thesis contributes to the existing body of knowledge in several ways. First, the analysis framework expands on methods primarily used in mode share analyses to explore potential changes in travel demand across added dimensions of time and space. Secondly, through the use of Google Maps travel data in a generalized cost analysis, this thesis investigates what the author understands to be a previously unexplored application of crowdsourced travel data. Lastly, this thesis demonstrates the application of the analysis framework on a set of study corridors in the Greater Toronto and Hamilton Area in Ontario, Canada, where similar assessments of TDM potential have not been used, with the exception of work previously conducted by the author in coordination with Casello & Yeung, (2016), which serves as a precursor to this work.

1.3 THESIS STRUCTURE

This thesis is organized into five major sections, including this introductory section. Section 2.0 presents a review of the literature to provide background on the history and origins of TDM within the North American context, existing TDM evaluation models, and data collection methods. Section 3.0 provides an overview of the analysis framework and describes the analysis methods employed. Application of the model and sample model results are presented in Section 4.0. Finally, a discussion of the model results and functionality, limitations, and opportunities for future research are included in Section 5.0. In addition to the main body of this thesis, two appendices have been included. Appendix A provides supplementary information relating to the methods used in the calculation of generalized costs in this application of the model. Appendix B presents the detailed results from this application of the model.

2.0 LITERATURE REVIEW

This thesis considers a set of methods for identifying opportunities where TDM policies, programs, and initiatives can be effectively employed at a corridor level, which represents travel demand between regional centres. In addition to building on existing evaluation methods, new data sources are considered in order to make the model more accessible to a broader user base. To inform the formulation of the model used in this thesis, a number of research questions have been posed, including questions pertaining to: the history of TDM and past models that have been used to evaluate the performance of TDM strategies; existing and emerging sources of data that can be used to improve the quality of TDM evaluations; and the effectiveness of a previously unexplored combination of methods and data in evaluating corridor level opportunities for TDM. This section seeks to answer some of the research questions by exploring the literature around the history of TDM in North America, past methods used in the evaluation of TDM initiatives, and data sources that have potential application in TDM analysis.

2.1 OVERVIEW

The concept of Transportation Demand Management (TDM) is well documented across both academic and non-academic literature. In the time that the concept has been in existence, practitioners – particularly in the United States – have adopted TDM strategies extensively within government plans, policies, and programs. The TDM strategies that have been put into application are many and varied, ranging from those that are site-specific, to others that have relevance over entire corridors and regions. The growing body of implementation examples have supported the development of a robust suite of post-implementation monitoring and performance measurement techniques. However, a review of the literature finds that methods to assess the suitability of strategies prior to implementation in the transportation network are less common. Given that execution of some TDM strategies can be costly, pre-implementation assessments are necessary to ensure that investments to enable TDM strategies are capable of producing effective results within the context which they are applied. The availability of new data sources also offers opportunities to strengthen existing methods.

This section of the thesis provides the background on the theories behind TDM and the history of how it emerged in the North American context. The literature related to methods of evaluation that have been used in the analysis of TDM are reviewed. Finally, the chapter presents a discussion of several data sources that have potential application within TDM analysis and evaluation.

2.2 TRANSPORTATION DEMAND MANAGEMENT AND BEHAVIOURAL CHANGE

Transportation Demand Management (TDM) encompasses a wide range of strategies that aim to alter travel behaviour, with the intent of reducing congestion and improving the performance and efficiency of the transportation system (Meyer, 1999; National Center for Transit Research, 2007; Wachs, 1990). Fundamental to this concept is the emphasis on the throughput of people instead of vehicles across the transportation network. At the time of its inception, this change in focus represented a marked shift away from the conventional transportation wisdom, which was catered towards the movement of vehicles (Meyer, 1999; Wachs, 1977). The concept is related to, but distinct from Transportation System Management (TSM), which targets improvements to system performance through changes to physical and operational design. Rosenbloom and Ferguson both succinctly differentiate TSM and TDM using the concept of supply and demand – TSM comprises strategies that directly change the supply, or capacity of the transportation system, while TDM comprises strategies that aim to shift or alter demand for travel within the transportation system (Ferguson, 1990; Rosenbloom, 1978). As congestion generally occurs when the capacity of a transportation system is exceeded by travel demand, these two strategies are complementary in their intents (Ferguson, 1990; Rosenbloom, 1978). Although the two terms are sometimes used interchangeably within the literature, this thesis adopts the characterization that has been set out by both Ferguson and Rosenbloom. TDM measures are also sometimes referred to as Transportation Control Measures (TCMs), particularly in the context of air quality.

TDM strategies motivate changes in travel behaviour primarily by altering how travellers value different travel options (Meyer, 1999; Taylor, Nozick, & Meyburg, 1997). These changes in behaviour include the use of alternative modes, travel during different times or along different routes, and overall reductions in the distance or frequency of travel (Federal Highway Administration, 2012; Nozick, Borderas, & Meyburg, 1998). Given this broad mandate, a wide variety of strategies can be associated with the concept of TDM. Within the literature, researchers have attempted to classify such strategies into a number of different categorizations. At a broad level, one common method of classification is to sort TDM measures as either 'hard' or 'soft'—hard strategies being those that motivate behavioural change through tangible changes to a traveller's utility or disutility, while soft measures are those that encourage behavioural change by influencing a traveller's perception or awareness of their available choices (Federal Highway Administration, 2012; Richter, Friman, & Gärling, 2011; Sunitiyoso, Avineri, & Chatterjee, 2010; United States Environmental Protection Agency, 2000b; Xing, Takahashi, & Kameoka, 2010). Hard TDM measures include strategies such as road tolls, road pricing, time-of-day fares, and parking charges. On the other hand, soft TDM measures tend to align more closely with community-based social marketing strategies and include techniques such as awareness campaigns, commuter challenges, facilitated carpool match-ups, and targeted and personalized traveller information.

Alternatively, TDM strategies can also be classified on consideration of their intended impact. TDM methods may attempt to supress travel demand, or to shift travel demand in space, time, or mode (Federal Highway Administration, 2012). In reality, strategies are often intersectional and have the capability of inducing travel behaviour changes in more than one way. As an example, variable congestion pricing on highway facilities, which would place a time and/or distance variable toll on users depending on the level of congestion experienced, could shift travel demand in time to periods when the congestion charge is less, or to parallel alternatives such as transit and local roads. An abundance of literature is available on the various TDM strategies and techniques used. The Federal Highway Administration, Institute of

Transportation Engineers, and Noxon Associates Limited (2012; 1989; 2008) all provide useful information on a broad selection of TDM strategies commonly used in practice.

2.3 TDM IN NORTH AMERICA

The 1970s have been characterized as a turning point in the field of transportation, when researchers and practitioners in the United States actively sought out concepts such as TDM and TSM as alternatives to continued spending on highway expansions (Ferguson, 1990; Meyer, 1999; Rosenbloom, 1978; Wachs, 1977, 1990). A number of circumstances of the time have been attributed to motivating the development of TDM strategies and the shift in paradigm towards the efficient movement of people instead of vehicles. Most notably, the 1970s marked a period of fiscal constraint in the United States, during which policy makers emphasized the importance of finding ways to manage traffic and reduce congestion without the need for additional spending on infrastructure (Meyer, 1999; Wachs, 1990). At the same time, public awareness of the environmental implications of heavy automobile reliance began to grow. Transportation related environmental concerns, such as air quality and energy conservation, became the focal point of policies at all levels of government (Meyer, 1999). In addition to this, the 1970s saw major disruptions to oil supplies from the Middle East, resulting in an increase in gas prices (Meyer, 1999). These events led to clear federal transportation policy directives in the United States to pursue demand management strategies.

The introduction of TDM in the Canadian context has not been as distinct, and its history has been markedly less documented within the literature. Nonetheless, the concept of TDM has also, though to a lesser extent, become ubiquitous within Canadian transport policy. One account by Stewart and Pringle (1997) suggests that the concept of TDM arrived in the Toronto region in 1991 after a member of the Metropolitan Toronto Council read about the concept of trip reduction and asked city staff to conduct further research. However, the notion of eroding the supremacy of the personal automobile within the transportation system had permeated the thinking of Toronto citizens and transportation and city planners long before the arrival of the terminology.

Coincidentally, the early 1970s has also been described by some as the turning point for transportation in the Toronto region. In 1971, Toronto citizens successfully stopped plans for the Spadina Expressway–an urban freeway that would have cut through and uprooted many built up neighbourhoods in the inner city–effectively bringing an end to the era of new freeway construction in the region (Stewart & Pringle, 1997). While the primary motivation for citizens' rejection of the expressway was to protect the quality of life within the inner city, air pollution and environmental concerns stemming from increased vehicular traffic became underlying arguments that helped to support the case (Robinson, 2011; Stewart & Pringle, 1997). As a result, early policies related to congestion management and reduced automobile use arrived predominantly in the form of public transit improvements and transit supportive land uses (Transport Concepts in Stewart & Pringle, 1997). Among these policies was a "centres and corridors" strategy for the Metro Toronto region, intended to relieve development and travel demand in the downtown core of the city by motivating the urbanization of a connected system of nodes in the region's boroughs. First introduced in the 1992 draft official plan for the Metro Toronto region, the core concepts of this strategy continue to resonate in subsequent plans in the Toronto area and beyond. The impacts of the approach remain clearly visible in the urban form of the region today (Hodge & Robinson, 2001; Stewart & Pringle, 1997).

In the present day, this type of polycentric development in the GTHA, which is characterized by a system of connected nodes, is being driven by contemporary policy. The provincial government's Places to Grow Growth Plan for the Greater Golden Horseshoe identifies key "Urban Growth Centres" across the region (Ontario Ministry of Infrastructure, 2012). Similarly, Metrolinx, the regional transportation authority for the GTHA, has developed the "Big Move" Regional Transportation Plan which, further to the nodes highlighted in the growth plan, identifies "Mobility Hubs" where major transportation investments are to be focused (Metrolinx, 2008).

Under the current policy environment of the GTHA, TDM is promoted most actively through a program called Smart Commute–an employer based TDM program focused on carpooling, and promotion of alternative modes such as public transit, cycling, and walking through social marketing and awareness campaigns. Transportation Management Associations (TMAs) under the Smart Commute banner exist across the region, and serve to coordinate TDM programs at a more localized sub-area level.

The provincial government has also installed a number of high-occupancy vehicle (HOV) lanes on freeways in the region to encourage higher per vehicle occupancy. HOV lanes limit access to non-vehicles that hold multiple passengers, typically greater than two to three passengers, in order to provide faster and more reliable travel as an incentive to drivers who do no drive alone in a single-occupant vehicle (SOV). Studies and pilot testing is currently being conducted to explore the potential of converting some of these HOV lanes to high-occupancy tolling (HOT) lanes, which would allow for unused capacity on the HOV lanes to be sold to SOV users at a toll charge.

2.4 TDM EVALUATION METHODS

TDM strategies vary greatly in cost, impact, and effectiveness depending on the context in which they are applied. As such, evaluation of TDM strategies serves an important function in supporting the implementation and preservation of TDM programming. TDM evaluation methods can largely be categorized into two major classes–*a priori* performance estimation and *ex post facto* performance measurement (Federal Highway Administration, 2012; Finke & Schreffler, 2004). *Ex post facto* performance measurement methods, which are applied post strategy implementation, are generally carried out with the aim of monitoring performance, and in many jurisdictions, are the basis upon which funding for TDM programming is allocated and sustained. On the other hand, *a priori* performance estimation methods are applied prior to implementation, and are typically used to support the selection of appropriate strategies and measures and to estimate potential impacts. In line with the objectives of this research, this review focuses on *a priori* performance estimation methods within the literature.

Although this *a priori* performance estimation can be accomplished to some extent using traditional travel demand modelling methods, such models typically rely on a substantial amount of data as input, and require specialized expertise to operate. A review of the literature finds that there are few *a priori* evaluation models available, and there is currently no standardized method for analysis. Researchers and practitioners alike have sought out a number of different ways to simplify the evaluation and performance estimation process for handling TDM strategies. Many of the analysis methods specific to TDM draw upon theories and techniques from other parts of the transportation discipline such as the conventional four-step travel demand model, but typically opt for greater simplicity and more accessible data requirements. Table 1 lists several TDM evaluation models that have been put into practice. The following sections provide a brief overview of the techniques that have been employed in each of the models.

Table 1 – Existing TDM Evaluation Models

TDM Evaluation Models	**Method of Evaluation**
FHWA TDM Model Federal Highway Administration Travel Demand Evaluation Model (United States Environmental Protection Agency, 2000a; Zhou, 2008).	pivot-point logit model and look-up tables
EPA COMMUTER Model Environmental Protection Agency COMMUTER Model (Federal Highway Administration, 2012; United States Environmental Protection Agency, 2005; Zhou, 2008)	pivot-point logit model and look-up tables
TEEM Model TDM Effectiveness Evaluation Model (Federal Highway Administration, 2012; Winters, Hillsman, Lee, & Labib Georggi, 2010; Zhou, 2008)	direct elasticities
TRIMMS Trips Reduction Impacts of Mobility Management Strategies (Federal Highway Administration, 2012; Winters et al., 2010)	direct and cross elasticities
CUTR WRTM Center for Urban Transportation Research Worksite Trip Reduction Model (Federal Highway Administration, 2012; Winters et al., 2004; Zhou, 2008)	neural networks

2.4.1 Logit Models

Logit models are a type of econometric model used to predict outcomes where dependent variables are discrete or categorical. In its most basic form, the logit model predicts the likelihood which one outcome is chosen out of dichotomous outcomes in the dependent variable (e.g. 0 and 1 or “Yes” and

“No”). Variations on the basic form, such as the multinomial logit model, allow for analysis in cases where more than two discrete choices exist.

The use of logit models in *a priori* TDM evaluation takes inspiration from the mode choice step of the 4-step travel demand model. Mode choice models are built on utility theory, borrowed from the field of economics (Koppelman & Bhat, 2006; Train, 2009). The theory is centred on the supposition that choices between competing alternatives are made on the basis of the value or utility each choice brings the decision maker, and that a rational individual is most likely to choose the alternative that carries the greatest value (United States Environmental Protection Agency, 2000b; Zhou, 2008). In transportation applications, and more specifically in mode choice models, alternatives are more often compared on the basis of their disutility, as decision makers are motivated to minimize the cost and time of their travel. Several examples within the literature apply a logit-based approach to the evaluation of TDM strategies, including the Federal Highway Administration TDM Evaluation Model (FHWA TDM Evaluation Model) and the United States Environmental Protection Agency COMMUTER Model (COMMUTER Model). Taylor et al. also applies a similar logit-based approach in their study of Syracuse, New York (1997).

The FHWA TDM Evaluation Model is one of the earliest examples of TDM modelling described within the literature and uses an adapted logit approach as the basis of its analysis. The model was developed in 1993 by Comsis Corporation for the FHWA as a way to analyze the trip reduction potential of TDM strategies and has been widely used throughout the United States (United States Environmental Protection Agency, 2000a; Zhou, 2008). Using two separate modules, the model is capable of evaluating both hard and soft TDM measures, employing a pivot-point logit approach for hard TDM measures that can be quantified as cost or time, and empirically derived look-up tables for soft TDM measures which are more difficult to quantify (United States Environmental Protection Agency, 2000b; Winters et al., 2010). The pivot-point logit model formulation is shown in Equation 1, and further described on Page 13.

The COMMUTER Model, first released in 2000 and then updated in 2005 (as COMMUTER 2.0), was developed by Cambridge Systems Inc. for the United States Environmental Protection Agency (EPA) in response to amendments of the 1990 Clean Air Act (Federal Highway Administration, 2012; United States Environmental Protection Agency, 2005; Zhou, 2008). The COMMUTER model improves upon the FHWA TDM Evaluation model by providing an improved user-interface, and similarly employs two separate methods for calculating responses to TDM strategies–the logit pivot-point model for hard strategies and empirically derived look-up tables for soft strategies (National Center for Transit Research, 2007; United States Environmental Protection Agency, 2000b).

The pivot-point logit approach used in the FHWA TDM Evaluation Model, the Commuter model, as well as in the TDM study by Taylor et al. is a variation of the multinomial logit model. Instead of requiring information about the cost and time components that make up the utility of a given mode, the pivot-point model requires only the starting shares of the modes under analysis and the incremental change in utility, presented in negative terms where further disutility is expected. One advantage of using the pivot-point logit model as opposed to a standard multinomial logit function is that it greatly reduces the data requirements of the model (United States Environmental Protection Agency, 2000a). The pivot-point logit model, as presented in the COMMUTER model documentation, is expressed mathematically in Equation 1.

Equation 1 – Pivot-Point Logit Model Formulation (COMMUTER model)

$$P'(j) = \frac{P(j)\ \times\ e^{\Delta U_j}}{\sum_{i=1}^{n}(P(i)\ \times\ e^{\Delta U_i})}$$

Where:

$i = mode\ i$
$j = mode\ j$
$P(j) = Starting\ share\ for\ mode\ j$
$P'(j) = New\ share\ for\ mode\ j$
$\Delta U_{j,} =\ Change\ in\ utility\ of\ mode\ j$
$P(i) = Starting\ share\ for\ mode\ i$
$\Delta U_i = Change\ in\ utility\ of\ mode\ i$

To complement the pivot-point logit model, look-up tables are applied in the evaluation of soft strategies that are more difficult to quantify, such as non-monetary employer TDM support programs and workplace policies such as alternative work hours (National Center for Transit Research, 2007; United States Environmental Protection Agency, 2000b; Zhou, 2008). The tables present relational factors developed from empirical research on a number of specific TDM measures to adjust the mode shares. To ensure that the sum of the mode shares across all modes considered does not exceed 100%, a share adjustment process is used to proportionately redistribute the mode shares to fit a total of 100% (United States Environmental Protection Agency, 2000b). Figure 1 provides an overview of the COMMUTER model structure.

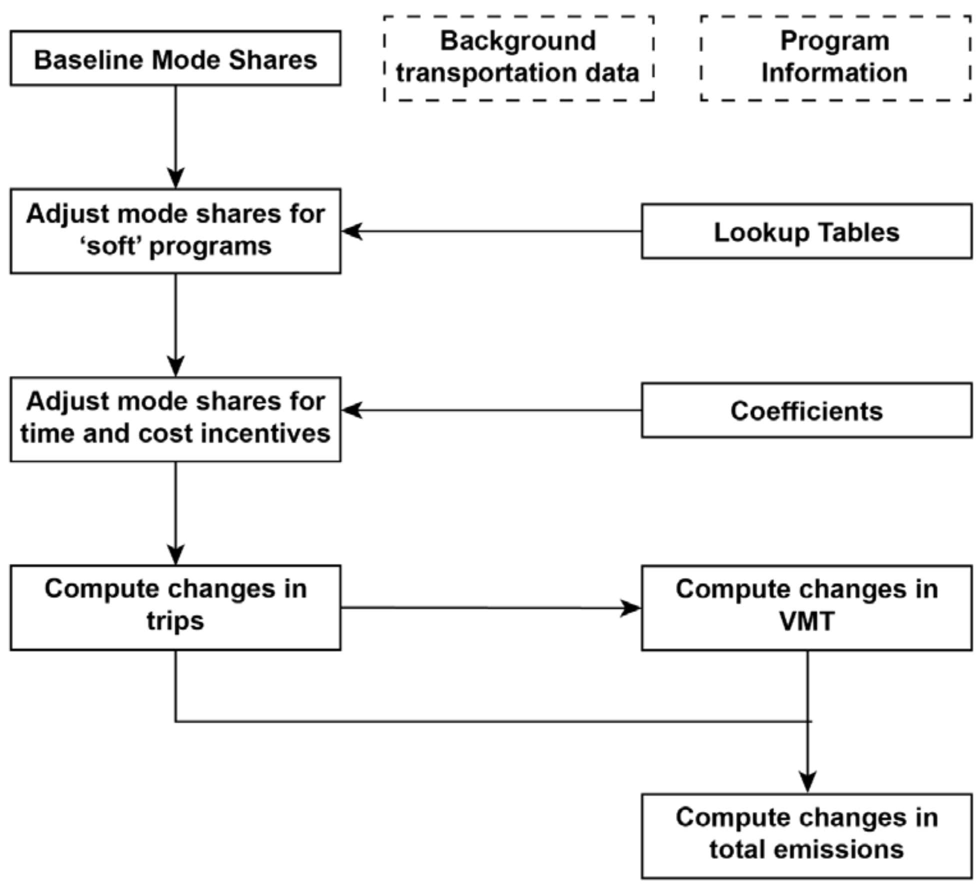


Figure 1 – COMMUTER Model Structure

In application, the COMMUTER Model makes adjustments to mode share using look-up tables first, prior to estimating mode share changes using the pivot-point logit model. Figure 2 illustrates an example of how the look-up tables are used. Building on a starting point of baseline mode shares, the COMMUTER Model adjusts mode shares for ‘soft’ programs according to the program level, or intensity, at which TDM strategies are applied for each mode. The look-up tables provide indication for the percentage change in mode share that is to be expected for each mode given the intensity at which the program is applied, and the change in mode share is then added to the base mode share. As the change in mode shares puts the total of shares across modes over 100%, an adjustment factor is used to scale the mode share values to sum to 100%. In cases where a given mode, in this case “Walk”, is not provided with a corresponding TDM support program, the COMMUTER Model holds the starting mode share constant through the adjustments so that it is protected from adjustments to the other modes (United States Environmental Protection Agency, 2000b).

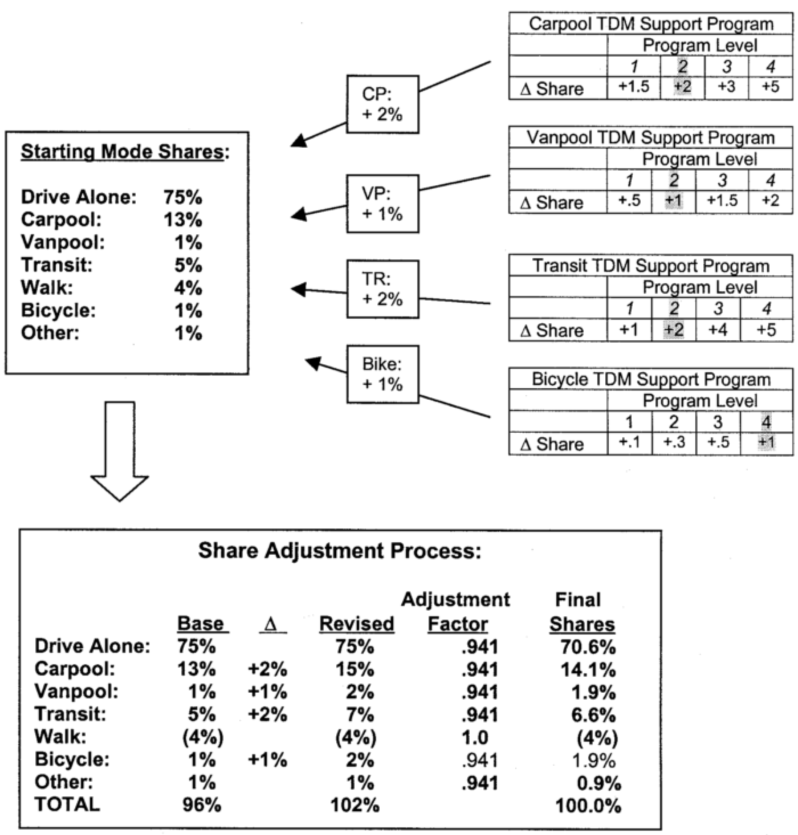


Figure 2 – Example of COMMUTER Model look-up table application

Once the mode shares have been updated for ‘soft’ programs, the pivot-point logit model is then used to further adjust the mode shares according to time and cost incentives presented. The degree of change in mode share for each mode is dependent on the change in utility of each mode, driven by a combination of the change in time and cost, as well as the model coefficients. Figure 3 illustrates an example from the United States Environmental Protection Agency on how the pivot-point logit model is applied within the COMMUTER Model (2000a). Only two modes, auto and transit, have been considered in this example, though the model formulation allows for inclusion of more than two modes. As the default coefficients in the COMMUTER Model are expressed in negative terms, any positive change in level of service (LOS) in the form of time and cost savings or benefits are expressed in negative terms. The resulting change, as expressed in a change in utility, is positive for savings in time or cost, and negative for additional costs incurred. In this example, a five minute reduction in transit travel times is presented as a negative change in LOS, for a total change in utility of 0.103 after the coefficient for transit travel time is applied. Given a starting mode share of 10% (or 0.10), and no change to the utility of auto travel, the pivot-point logit model estimates that the mode share for transit would increase to 11% in response to the travel time reduction.

Utility change: $\Delta U = \text{Coefficient} \times \text{Change in LOS}$

Transit utility change: $\Delta U_{Trans} = (-0.207) * (-5) = 0.103$

New transit mode share:

$$P'_{Trans} = \frac{P_{Trans} \times e^{\Delta U_{Trans}}}{(P_{Auto} \times e^{\Delta U_{Auto}}) + (P_{Trans} \times e^{\Delta U_{Trans}})} = \frac{0.10 \times e^{0.103}}{(0.90 \times e^{0}) + (0.10 \times e^{0.103})} = 11.0\%$$

where

P'_{Trans} = new transit mode share
P_{Trans} = base (existing) transit mode share
P_{Auto} = base auto mode share
ΔU_{Trans} = transit utility change
ΔU_{Auto} = auto utility change

Figure 3 – Example of COMMUTER Model pivot-point logit model application

A major benefit of the methods used in the FHWA TDM Evaluation Model and COMMUTER Model is simplicity and ease of use. The COMMUTER model in particular, is designed for an audience of practitioners and employers who are not expected to have an in depth technical background in travel demand modelling (National Center for Transit Research, 2007; United States Environmental Protection Agency, 2005). Although the model techniques are significantly less computationally intensive than other methods, such as the conventional four-step travel demand model, given the modest change in mode shares typically generated by TDM strategies, the model is considered to be accurate at least at a sketch planning level (National Center for Transit Research, 2007; Winters et al., 2010). However, the model results are largely dependent on pre-specified parameters that are either built into the default model set up, or inputted by the user. As a result, the accuracy of the model is heavily dependent on the calibration and quality of the underlying data on which the model is built (National Center for Transit Research, 2007; Winters et al., 2010). The logit-based model structure that is used also assumes that the choices available are mutually exclusive, without accounting for potential interactions between choices. Choices must also begin with a non-zero share in order for the model to operate properly given the structure of the mathematical formulation. Lastly, the model is unable to distinguish between short run and long run effects, and makes estimates purely on a “with” or “without” basis instead of considering the strategy with respect to time (Winters et al., 2010).

2.4.2 *Elasticities*

Elasticities measure the sensitivity of a variable to change given changes in the value of other variables. In economics, a common application of elasticities is in expressing the expected change in demand for a good given the underlying change in price. This concept transfers easily to TDM and transportation as it aligns with utility theory and the thinking that travellers make decisions about their travel given the value they assign to different transportation options. Within the literature, two models were found to use elasticities as the basis of analysis. The first is the Washington State TDM Effectiveness

Estimation Methodology (TEEM), and the second more recent model is the Trip Reduction Impacts of Mobility Management Strategies (TRIMMS) model (Winters et al., 2010).

The TDM Effectiveness Evaluation Model (TEEM) was developed for the Washington State Department of Transportation to assess the effectiveness of TDM and land use strategies in the Central Puget Sound Region (Federal Highway Administration, 2012; Winters et al., 2010; Zhou, 2008). TEEM is an elasticity-based spreadsheet model that uses direct price and service point elasticities to estimate changes in the number of vehicle trips from the implementation of TDM measures (Federal Highway Administration, 2012). Developed from local data sources, the model is capable of estimating the impacts of 20 different TDM and land use strategies at a corridor and sub area level, and has distinct evaluation methods for each one (Winters et al., 2010; Zhou, 2008).

While multinomial logit-based models like the COMMUTER Model can capture the impact of interactions between various TDM strategies, elasticity-based models like the TEEM model typically do not have the same innate capability (Federal Highway Administration, 2012). To compensate for this, the TEEM model includes assumptions about interactions across select strategies and methods for modifying the overall impact. When more than one strategy is tested, the model applies sensitivity factors to the base mode shares incrementally and adjusts the value of these factors based on the relationship (Winters et al., 2010). This adjustment method allows the model to more accurately represent two key types of strategy to strategy interactions: directly additive interactions and multiplicatively additive interactions. Strategies that are directly additive have no interaction, and their impacts are realised independently (Winters et al., 2010; Zhou, 2008). Under circumstances where strategies with a directly additive relationship have been chosen, no adjustment is made to the sensitivity of the base mode shares in the model (Winters et al., 2010; Zhou, 2008). On the other hand, strategies that have a multiplicatively additive relationship can interact and alter how the TDM strategies impact trip demands in combination. Sisinnio & Winters present an example of a multiplicatively additive relationship where two strategies both target the share of single-occupancy vehicles (SOV) (2009). In this example, one strategy, such as a transit subsidy, decreases SOV shares by 5%, while another strategy, such as parking charges, reduces SOV shares by another 7%. To prevent overestimation of the combined effect of the two strategies, the TEEM model recognizes a multiplicatively additive impact of 11.5% (100% - ((100% - 5%) x (100% - 7%))) rather than an additive impact of 12% (100% - 5% - 7 %).

In the TEEM Model procedure, sensitivity factors are applied with each additional multiplicatively additive strategy to readjust the base mode shares so that the model more accurately captures the combined effects (Winters et al., 2010). A shortcoming of this adjustment method and the TEEM model is that it is unable to capture conflicting or synergistic interactions between strategies. As such, users of the model must be cognizant of conditions that could result in these types of interactions and make adjustments outside of the model (Zhou, 2008).

The more recently developed TRIMMS model, first released in 2007 and last updated to version 3.0 in 2012, attempts to build on the strengths of the TEEM model (Federal Highway Administration, 2012). The model was developed by the Centre for Urban Transportation Research (CUTR) under the National Centre for Transit Research (NCTR) (Winters et al., 2010). Although TRIMMS similarly relies on elasticities for the core of its analysis, the model employs a different strategy for handling interactions than the TEEM model. Instead of assuming an additive or multiplicative relationship between interacting strategies, the TRIMMS model employs cross elasticities in addition to direct elasticities (Winters et al., 2010). While direct elasticities simulate the percentage change in the trip demand for a given mode that results from a change within its own price, cross elasticities simulate the change in trip demand for a given mode as a result of changes in the price of competing modes, which enables assumption of some degree of substitution of demand across modes (Federal Highway Administration, 2012; Winters et al., 2010).

Another unique feature of the TRIMMS model is that it provides direct consideration for indirect soft strategies, such as employer-based program support strategies, which do not have a tangible effect on travel time or travel cost, but contribute positively to the attractiveness of a mode (Sisinnio & Winters, 2009). The model considers three classes of employer-based program support strategies: TDM program support, such as rideshare matching and emergency ride home programs; alternative work schedules, which include strategies such as compressed work weeks, telecommuting, and flexible work hours; and worksite TDM oriented amenities, including the provision of on-site childcare facilities, bike lockers, and showers (Sisinnio & Winters, 2009; Winters et al., 2010). After the hard program impacts are estimated using the model elasticities, an adjustment procedure is used to modify the final vehicle trip rates according to relationships between the hard and soft programs (National Center for Transit Research, 2007, 2012; Sisinnio & Winters, 2009). The interactions between strategies are established through hedonic regression of empirical data, and in the case of the default TRIMMS model, the data were obtained from the Washington State Department of Transportation Trip Reduction Program for consecutive years from 1995 to 2005. (National Center for Transit Research, 2007; Winters et al., 2010).

As with the logit-based models, elasticity-based models are built with the aim of being simple and user-friendly. However, a major criticism of models that rely on elasticities is that they are less able to account for the complexities associated with interactions among available modal options. As an example, logit-based models, such as the COMMUTER model, are able to recognize that some TDM measures may inadvertently draw demand away from modes other than single-occupancy vehicles, whereas elasticity based models are less equipped to handle these shifts. It is also more difficult to assess the interactive effects of multiple strategies at once within elasticity-based models as impacts are layered on incrementally. (Winters et al., 2010). The developers of the TRIMMS model assert that they have overcome some of these challenges by including the use of cross elasticities in addition to direct elasticities (Winters et al., 2010).

2.4.3 Neural Network Models

Neural network models, or artificial neural network models, are a type of computing system that is used to process information by inferring rules and relationships from existing data. It is commonly associated with artificial intelligence and machine learning, and is loosely designed to resemble the structure of synapses and neurons in the brain. The CUTR Worksite Trip Reduction Model (WTRM) is one TDM evaluation model that uses neural networks as the basis of analysis. The model was developed in 2004 by the Center for Urban Transportation Research (CUTR) at the University of South Florida for the Florida Department of Transportation and the United States Department of Transportation (Federal Highway Administration, 2012; Zhou, 2008). The model is designed to predict the impact of packages of TDM measures and has the built in function to consider the over 100 individual TDM strategies (Federal Highway Administration, 2012). Unlike the other models, which were aimed at estimating shifts in mode share, the dependent variable of the WTRM is vehicle trip rate, making overall traffic reduction the core emphasis of this model (Winters et al., 2004).

Harnessing the capabilities of neural network formulation, the WTRM analyzes data from worksite travel plans to develop average changes in vehicle trip rate (Federal Highway Administration, 2012). Model development for the WTRM combined two approaches: linear statistical regression, and non-linear neural network formulation. The neural network formulation makes up the core of the analysis model while the linear regression model was used as a benchmark to validate the accuracy of the neural network model (Winters et al., 2004; Zhou, 2008).

The WTRM was developed from a large database that contained several thousand records of data from worksite trip reduction programs in southern California, Tucson (Arizona), and Seattle (Winters et al., 2004, 2010). All three areas have had longstanding trip reduction requirements for employers, which have generated an abundance of data suitable for training a neural network model (Zhou, 2008). The model takes inputs such as a worksite's company characteristics, available alternative modes, incentives and disincentives, alternative work arrangements, and the worksite location in order to estimate an output vehicle trip rate (Winters et al., 2004). Figure 4 provides an illustration of the WRTM structure.

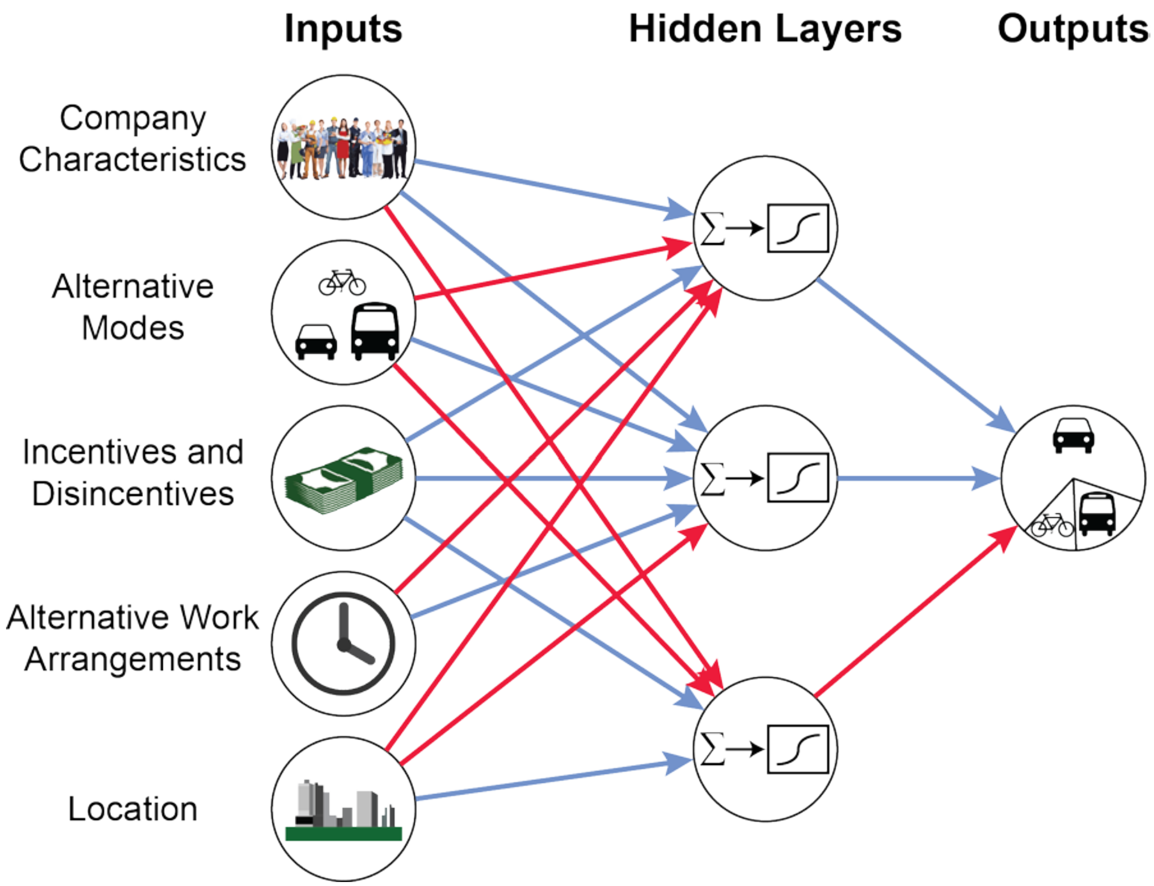


Figure 4 – WTRM neural network structure (adapted from Winters et al., 2004)

Winters et al. (2010) conducted a comparison between the WTRM and COMMUTER model using over 450 records from the Seattle dataset. The results showed that the WTRM tended to under predict changes in vehicle trip rate while the COMMUTER model generally over predicted the vehicle trip rate change. Overall, the comparative analysis showed that the WTRM results more closely matched survey results than those predicted using the COMMUTER model. However, one downside of neural network models such as the WTRM is that they are data intensive. The more data that are used to train the model, the more accurate the outcomes—a comparison of the WTRM using data from all three jurisdictions outperformed a model that was built on data from southern California alone (Federal Highway

Administration, 2012). Over time, with more worksite trip reduction data available, models such as WTRM may be trained to become even more accurate.

2.5 TRANSPORTATION DATA COLLECTION

As exemplified by the overview of TDM evaluation models in the previous section, data relating to the conditions of travel, such as travel times, travel costs, existing mode shares, and traveller behaviour are critically important regardless of the analysis method used. Conventional methods for collecting travel data typically involve the use of traveller surveys, which can be time-consuming and resource intensive (Minal, 2014). The GTHA and broader Greater Golden Horseshoe Region have been fortunate to have a comprehensive source of data available through the Transportation Tomorrow Survey (TTS).

The TTS is a regional traveller survey that is jointly funded by local and provincial government agencies. The survey has been conducted and managed by the Data Management Group at the University of Toronto since 1986 and is used widely across the region and serves as the basis for much of the analysis conducted. (Roorda & Shalaby, 2008). The TTS began in the form of a telephone interview that was conducted every five years through a sampling of listed residential telephone numbers (Data Management Group, 2014). However, this has proven to be troublesome over time with increased use of mobile phones, and a corresponding decrease in the use of landline phones. Originally identified as a concern in the 2006 iteration of the TTS, the growing pervasiveness of mobile phones manifested underrepresentation of the 18 to 29 age cohort by 30% in the 2011 TTS, compared to 20% in the 2006 TTS (Data Management Group, 2014; Roorda & Shalaby, 2008). In the most recent iteration of the survey, TTS 2016, the Data Management Group has attempted to address the issue of under-representation among younger populations by offering the option of survey completion over the internet.

Roorda & Shalaby (2008) provide a detailed account of the data collection challenges and opportunities that they expect to encounter in the near future including: the growing obsolescence of landline phones; increased use of mobile phones and voice over internet protocol (VoIP); and the increased use of Global

Positioning Systems (GPS) and ITS-based data collection techniques that could serve as tools to supplement existing data collection methods. Although the TTS provides valuable information on many aspects of transportation behaviour and travel conditions in the region, one piece of data that is missing are travel times. In its guidelines for measurement of TDM initiatives, Transport Canada (2009) encourages the collection of travel times as part of determining baseline conditions. While other traveller surveys similar to the TTS may include questions relating to the travel times experienced by interviewees, self-reported travel times are inherently biased by the subjective perception of the traveller (Klöckner & Friedrichsmeier, 2011; Levinson, Harder, Bloomfield, & Winiarczyk, 2004). Travel times currently used in travel demand models in the region typically rely on modelled congested link travel speeds, generated on modelled networks during the traffic assignment step of the four-step travel demand model (P. Kucirek, personal communication, June 21, 2017). However, the emergence of new technologies and techniques may offer up opportunities for collecting travel time data that is more reflective with actual conditions.

As it stands, there are at least two methods of data collection that show promise for improving the collection of trip level travel time data. The first is through the application of Global Positioning System (GPS) surveys in tandem with the conventional travel survey. The other is to use locational data that is crowdsourced from cellular phones. The following sections explore these two data collection methods in further detail.

2.5.1 Global Positioning System (GPS) Surveys

GPS surveys have seen substantial use in the field of transportation since the first passive GPS study was conducted as part of a household travel survey for Austin in 1997 (Casas & Arce in Minal, 2014). There is an abundance of literature about the use of GPS surveys to track trip related information such as trip traces and travel time, along with recording of other travel related attribute information. For example, Wolf, Guensler, & Bachman (2001) attempt in their study to derive information about trip purpose from a GPS study involving data loggers, while Nour, Casello, & Hellinga (2010) have proposed a set of methods for using GPS data as a means for better understanding transit traveller anxiety while in travel.

Studies involving the use of GPS typically require survey participants to carry a GPS data logger for the duration of the study (Minal, 2014). Modern GPS data loggers are capable of recording granular second-by-second location, position, and travel speed data to a resolution or accuracy of several meters (Moiseeva & Timmermans, 2010; Wolf et al., 2001). A major benefit of GPS surveys is the ability to counter the effects of self-report error inherent to conventional travel surveys (Stopher, Clifford, Swann, & Zhang, 2009). Under-reporting of trips in travel survey diaries has been estimated at as little as 7.4% of trips to as much as 30% of trips (Stopher et al., 2009; Stopher, FitzGerald, & Xu, 2007). Researchers report that trips missed in travel survey diaries tended to be short, made after 5 PM, and connected to activity locations at which respondents remain for only short periods of time (Stopher et al., 2007). In a study by Stopher et al. (2007) which compared the results of GPS surveys to household travel surveys conducted face-to-face, over the phone, and over the internet, it was found that while the start and end times of trips matched quite well between the GPS data and travel survey responses, the number of trips made, the distance that is travelled, and the travel time taken showed observable discrepancies. The study also found that travellers were about twice as likely to over report the distance and time they spent in travel than to under report it (Stopher et al., 2007).

Another benefit of GPS surveys is that the data can be easily associated with additional characteristics of the subject or participant to provide a fuller perspective on the behavioural aspects of travel. However, due to the cost of administering GPS data loggers to survey participants, there are obvious financial limitations to sample size (Cottrill, Dias, Lim, Ben-Akiva, & Zegras, 2013). Although survey data are typically anonymized, small sample sizes may resultantly deter some travellers from participating out of concern that their personal information could be more easily discernable. The reciprocal effect is the potential self-selection bias among those travellers who agree to participate in the GPS survey (Minal, 2014). The use of administered GPS data loggers also means that survey participants must actively remember to carry the device with them during travel for the duration of the survey (Cottrill et al., 2013; Stopher et al., 2009). As carrying an extra GPS device is outside the usual habits of most travellers, it is possible that some participants may overlook the need to carry the device on some trips, which would similarly result in under reporting of trips (Nour, Hellinga, & Casello, 2016). On the other hand, hyper awareness of the GPS data logger and the travel behaviour that is being recorded could also have the effect of making survey participants respond differently, resulting in recorded travel behaviours that are not reflective of their natural behaviour (Kim, 2015).

2.5.2 Smartphone Based Travel Surveys

A more recent advancement on GPS surveys is the use of smartphones in place of administered GPS data loggers. As smartphones have become increasingly ubiquitous, its usefulness as a means for gathering travel data has become more apparent. One of the earliest smartphone travel surveys was conducted in 2007 by the University of South Florida as a way to collect travel behaviour data (Barbeau, Labrador, Georggi, Winters, & Perez, 2009; Ferrer & Ruiz, 2014). Since then, the body of research around the use of smartphone travel surveys has grown substantially, and a number of commercial tools have also become available to support such mobility studies (Cottrill et al., 2013; Montini, Prost, Schrammel, Rieser-Schüssler, & Axhausen, 2015).

Similar to GPS travel surveys, a common application for smartphone based travel surveys is in the detection and recording of trip related information. Although a comparison between dedicated GPS device data and smartphone data by Montini et al. found that many smartphones tended to have lower sampling frequencies than dedicated devices, the level of detail is sufficient for most trip or route detection required in travel surveys (2015). In more sophisticated applications of the technology, researchers have also attempted to infer information, such as the mode of travel, by using GPS in combination with other sensors and systems built into most commercially available smartphones like the accelerometer (Ferrer & Ruiz, 2014; Nour et al., 2016). A number of different methods, including rule-based models and machine learning have been employed to infer certain trip characteristics.

Smartphone based travel surveys typically involve the use of a mobile application which participants are required to keep running on their smartphones for the duration of the survey. In some cases, contextual information is collected through pre-surveys as participants are registered, and in follow-up exit surveys, as in the case of the Future Mobility Survey (FMS), conducted in Singapore as a subset of the broader Household Interview Travel Survey (HITS) (Cottrill et al., 2013). This information is used to help improve the accuracy of finding inferred from the collected data, and may include information about the traveller such as demographics and vehicle ownership, as well as key points of interest and frequently visited places (Cottrill et al., 2013). Some applications also require participants to validate the data that is recorded in real-time through prompts within the application.

An obvious benefit of smartphone based travel surveys is the reduced cost. As most travellers own their own personal smartphone devices, there is no need for dedicated GPS devices to be administered (Ferrer & Ruiz, 2014; Nour et al., 2016). The pervasiveness of smartphones also opens up a large pool of potential participants who can join a survey without being provided a device, and as a common everyday item, smartphones are also less likely to be left at home than a dedicated GPS device that a person is not accustomed to carrying on a day to day basis (Montini et al., 2015).

Similar to dedicated GPS devices, location enabled smartphones allow for a high degree of accuracy in recording trip related data such as trip times, locations, and paths. An added benefit of smartphone based surveys is the ability to gather and provide real-time feedback to survey participants. Unlike GPS surveys, which typically require follow-up surveys to gather further information or validation from travellers, smartphone applications can integrate these queries through the same interface (Cottrill et al., 2013; Montini et al., 2015). Further to this, the presence of complementary technologies such as accelerometers, WIFI, and Global System for Mobile Communications (GSM) make smartphones useful in other regards, such as trip detection and mode estimation (Nour et al., 2016; Safi, Assemi, Mesbah, & Ferreira, 2016).

However, a drawback of smartphone based travel surveys is that similar to GPS surveys, participation is voluntary, which may introduce self-selection bias. Cottrill et al.(2013) describe their experience using smartphones in the FMS, where participants were offered a cash incentive of approximately $25 USD to participate. Even with the incentive, the survey saw a significant drop out rate. From the initial 74 participants recruited, less than 50% actually downloaded the mobile application to enable data collection, and in the end, only 36% of participants actually validated their data after the fact. Though it was also observed that many of those participants who remained active in the study contributed in validating data well beyond the minimum amount of days they were asked to by surveyors, suggesting that some participants may have been significantly more interested in the survey process than others.

The rate of drop out among participants, as exemplified in the FMS survey described by Cottrill et al (2013), also points to an issue around participant burden. While much of the data collection process can be done passively, additional data collected through the user interface of the mobile application that require user feedback and validation can make the experience more onerous. The more detailed the data are, the higher the potential burden on survey participants (Patterson & Fitzsimmons, 2016).

In addition to the potential inconvenience that participants may experience from any active feedback required of them during the survey process, consumption of participant resources in the form of battery drainage and use of a participant's mobile data plan have also been noted as major considerations in many studies (Cottrill et al., 2013; Jariyasunant, Sengupta, & Walker, 2012; Montini et al., 2015; Patterson & Fitzsimmons, 2016). As participants are likely to use their smartphones for other purposes throughout the course of a day, it is important that survey applications do not consume resources in a way that compromises participants' ability to use their phone for other functions. While survey participants are less likely travel without their personal smartphone devices than a dedicated GPS device, data may similarly be missed if users carry their smartphones but do not turn on the survey application in order to conserve battery and data (Montini et al., 2015). As a result, the trade-off between data need or accuracy and resource consumption is an important one, and some researchers have sought out application designs that minimize resource consumption through specified sleep/wake patterns and other battery optimizing techniques (Cottrill et al., 2013; Safi et al., 2016).

2.5.3 Crowdsourced Travel Data

A number of different web map applications rely on crowdsourced information from smartphones and connected devices to inform travellers of expected travel times and optimal routing. Socharoentum & Karimi (2015) explore several web map applications including Google Maps, which is well used in North America. According to grey literature, Google provides estimates of travel times based locational data sourced from mobile devices (Schwartz, 2010). The travel speeds and location information are compiled to establish time of day and time of week travel patterns that are used in predictive results (Google, 2009, 2010). Since this capability was made available to the public in the late 2000s, a number of studies have noted the use of Google Maps data, and other similar web mapping applications, for estimating transport travel times and route recommendations, including X. Wang & Cui (2017), Owen & Levinson (2015), Eluru, Chakour, & El-Geneidy, (2012), and F. Wang & Xu (2011).

The study by Wang & Xu (2011) is one of few, if not the only study to date, to conduct a direct comparison of Google Maps generated travel time data to conventional travel time modelling methods. The analysis compared travel times estimated using the Google Maps API to travel times generated by conventional network modelling techniques, in this case the Network Analyst tool from ArcGIS (Wang & Xu, 2011). The authors found that while both methods generated travel times that were highly correlated to the Euclidean distance between origin and destination (both methods yielded R^2 values of 0.91), the Google data had a larger y-intercept at 4.68 minutes compared to 0.79 minutes for the modelled data. The researchers suggest that the additional time accounts for the time spent by travellers getting to and from the road network at the beginning and ends of a trip—which aligns with behaviour that is often captured in empirical data, but not captured in the modelled data. Wang & Xu (2011) also found from their study that the percentage difference between the modelled data and the Google Maps reported travel times decreased exponentially with increase in distance.

Based on the research available to date, there are several obvious benefits to using crowdsourced travel time data from applications such as Google Maps. Unlike conventional methods of network travel time modelling, data collection from Google Maps does not require the creation of a detailed network dataset, which saves a significant amount of time and data resources (Morgul et al., 2014; Owen & Levinson, 2015; F. Wang & Xu, 2011). The data that inform the Google Maps' travel time estimations, including the cellular location data that are collected, are collected passively and more frequently updated than the data used in conventional models, such as traveller surveys or GPS studies, which typically occur only once every several years (F. Wang & Xu, 2011). Lastly, while modelled networks typically rely on posted speed limits and peak period volumes to inform estimates of congested travel time, Google Maps data account for "real-time" congestion, reflecting the actual travel conditions experienced by travellers across different times of day, not limited to the peak periods (F. Wang & Xu, 2011).

However, use of crowdsourced data is not without its challenges and limitations. For one, the data are maintained exclusively with little transparency into quality control or the algorithms used to determine route recommendations. Although Google Maps has generally been reputed for maintaining its data at a high level of quality, data are hardly ever perfect, and not knowing the limitations of a certain data set is a cause for concern (F. Wang & Xu, 2011). Since the data collected from Google Maps are anonymized, the travel information retrieved is detached from the context of the users who generate the data points, making it less suitable for behaviour research than methods such as GPS surveys. Lastly, parts of the Google Maps data, such as the transit routing data, relies on the contributions of individual transit agencies who are responsible for uploading data about their services in the form of General

Transit Feed Specification (GTFS). As such, queries to the system relating to transit travel is limited by the quality of the data provided by the transit agencies.

2.6 CHAPTER SUMMARY

TDM as a category of policies, programs, and initiatives emerged out of a shift in paradigm from an emphasis on the movement of cars and vehicles to a focus on city-building and the effective movement of people and goods. A number of forces, including a growing awareness around environmental issues, an increase in fuel prices, and government fiscal constraints contributed to the rise of TDM as a major tool in the transportation professional's toolbox.

Since the concept of TDM first emerged in North America during the 1970s, a number of *a priori* methods of evaluation have been tried. One of the oldest and most used is the logit model, which draws from the mode choice step of the conventional four-step travel demand model. Examples of this include the FHWA TDM Evaluation Model, which is one of the oldest *a* priori TDM evaluation model documented, and the COMMUTER Model, which represents a more recent application of this method. Other methods include the use of elasticities, such as in the TEEM and TRIMMS models, and neural network models, as in the case of the WTRM. The WTRM is the most advanced out of the models explored, and stands to improve as more TDM program related data is generated over time. However, as development of neural network models such as the WTRM require a high degree of specialized expertise and rely heavily on data from existing TDM strategy use cases, it is less suitable for application in contexts with limited resource and little past experience in TDM application. Elasticity-based models such as TEEM and TRIMMS are much simpler, and require little prior training to execute. However, similar to neural network models, elasticity based models are also informed by existing data on the post-implementation performance of TDM strategies. In contrast, logit based models are less data intensive, relying on coefficients within the utility function to determine how various TDM strategies in the form of time and cost changes are valued.

Data relating to the conditions of the transportation system are important in informing transportation analyses. Conventional methods of data collection such as travel surveys continue to be used, but are limited by their ability to reach certain parts of the population and are plagued by issues related to self-reporting. Location-enabled technologies such as GPS devices and smartphones have proven to be better suited for detailed documentation of trip related data, and show promise in supplementing or replacing conventional travel surveys. However, challenges associated with self-selection bias, hyper-awareness from survey participants and battery drain remain to be solved. As an extension of data collection via smartphones, there is also a growing body of research around the use of crowdsourced travel data, collected passively from smartphones and other connected devices rather than actively from participants through a mobile application. Though crowdsourced data cannot completely replace travel surveys as it lacks contextual data about the traveller, it benefits from having a large sample size and sampling period. The granularity of crowdsourced travel data available makes it an attractive option for informing transportation analyses such as corridor level analyses based around utility calculations.

3.0 METHODS

The selection of appropriate TDM strategies requires identification of opportunities and evaluation of policies, programs, and initiatives prior to implementation. While conventional travel demand forecasting models are capable of evaluating the expected performance of TDM measures, practitioners serve to benefit from focused models that can help to highlight opportunities and use more nimble methods of analysis and accessible sources of data.

Section 2 of this thesis provided an overview of the history and background surrounding TDM in North America. A review of the literature uncovered several techniques that have been used in the past for TDM evaluation. While models that employ elasticities and neural networks rely heavily on insight gained from past implementation of TDM strategies, models that use methods such as the logit model can be built off of more general data on the conditions of travel and traveller behaviour. With advancements in data collection technology and techniques, emerging data sources such as crowdsourced travel data can provide a clearer picture of the conditions on which TDM measures may be applied.

This chapter describes a model framework developed to identify and evaluate opportunities for TDM strategies to be applied. Detailed descriptions are provided on how each step of the model is executed, along with explanations of the model formulations and variables used.

3.1 OVERVIEW

The model developed through this research is intended as a tool for transport practitioners to recognize travel corridors for opportunities to apply TDM measures. It takes inspiration from the mode-choice step of traditional four-step travel forecasting models employing the logit model to estimate the probability that travellers will choose each mode based on a set of known conditions and variables. In essence, the model is designed to compare the relative utility or disutility associated with different modes, along different routes, and at different times of day to identify conditions under which alternative times, routes, and modes of travel are competitive to the prevailing mode. Consider a trip that is typically made between a set origin and destination, with an intended arrival time of 9:00 AM, which uses private auto on a route that traverses both local roads and freeways. Alternatives to this travel behaviour, without altering the origin and destination location, are to travel and arrive at a different time, travel on a different route, or use a different mode. Under the presumption that travellers are motivated to maximize their personal utility and would most likely choose the mode, route, and time of travel that affords them the least amount of disutility, a traveller would only willingly consider other alternatives to their current behaviour that come at a comparable or lower cost. Where alternatives are closely comparable, minor incentives and disincentives introduced through application of TDM measures can potentially help to make less competitive alternatives more competitive.

With improved understanding of the corridor level dynamics, appropriate TDM strategies can then be selected and tested within the logit model to approximate the level of change that will have to be induced in order to motivate behavioural change. Instead of relying on traditional data sources such as household travel surveys, this model uses data that are widely accessible such as crowdsourced travel data accessed through Google Maps. Applying relatively simple techniques and data that are easy to acquire, it is anticipated that this sketch model will be applicable to a broad range of contexts. Alternatively, this sketch model may also be useful to support decision making on matters of TDM in jurisdictions that do not have ready access to traveller survey data, a regional travel demand model, or lack the in-house capabilities to modify and run such complex models.

The following sections describe the techniques used in the model. Section 3.2 outlines the structure of the model. Section 3.3 provides guidance on the generalized cost calculations. Sections 3.4 and 3.5 describe the first module of the model which is used in the identification of travel demand challenges, while sections 3.6 and 3.7 describe the second module, used to estimate the demand shifting potential of test TDM strategies selected.

3.2 MODEL STRUCTURE

The model is structured to accomplish two main tasks. The first goal is to identify the travel demand challenges impacting the corridor under analysis while the second objective is to estimate the potential demand shifting capability of strategies selected for application. Both processes employ generalized costs calculated from trip data—in this case, sourced mainly from commercially gathered data, which in this application are from Google Maps. Generalized costs are used as a way to represent the utility of a given transportation alternative. Calculations of generalized cost typically account for a number of time and cost variables related to one's travel, including the cost of time spent both in-vehicle and out-of-vehicle during travel, as well as any monetary costs incurred, such as the cost of fuel, transit fares, parking, and tolls. The formulation of the generalized cost functions used in this analysis is described further in section 3.3. Figure 5 shows the sequence of the analysis procedures used within the model.

The first part of the analysis builds on previous work developed by Casello, Chiu, & Yeung for Metrolinx, and presented at the 95th Annual Meeting of the Transportation Research Board (2016). The module is used to screen and identify corridors for challenges and opportunities to employ TDM initiatives by comparing the cost of available alternatives. The model begins with the calculation of generalized costs from trip data. These generalized cost values are then used in the calculation of competitiveness ratios, which serve as the basis of a comparative analysis that helps users to identify where there are opportunities for travel demand to be shifted in space, time, and mode within the corridor. Competitiveness ratios, as described in section 3.4, compare the generalized costs of competing alternatives and provide an indication of how attractive an alternative or choice is compared to a specified base alternative, typically an alternative by auto at the specified time of analysis. With an understanding of the opportunities available for TDM application, the user can then select potential TDM strategies for further testing.

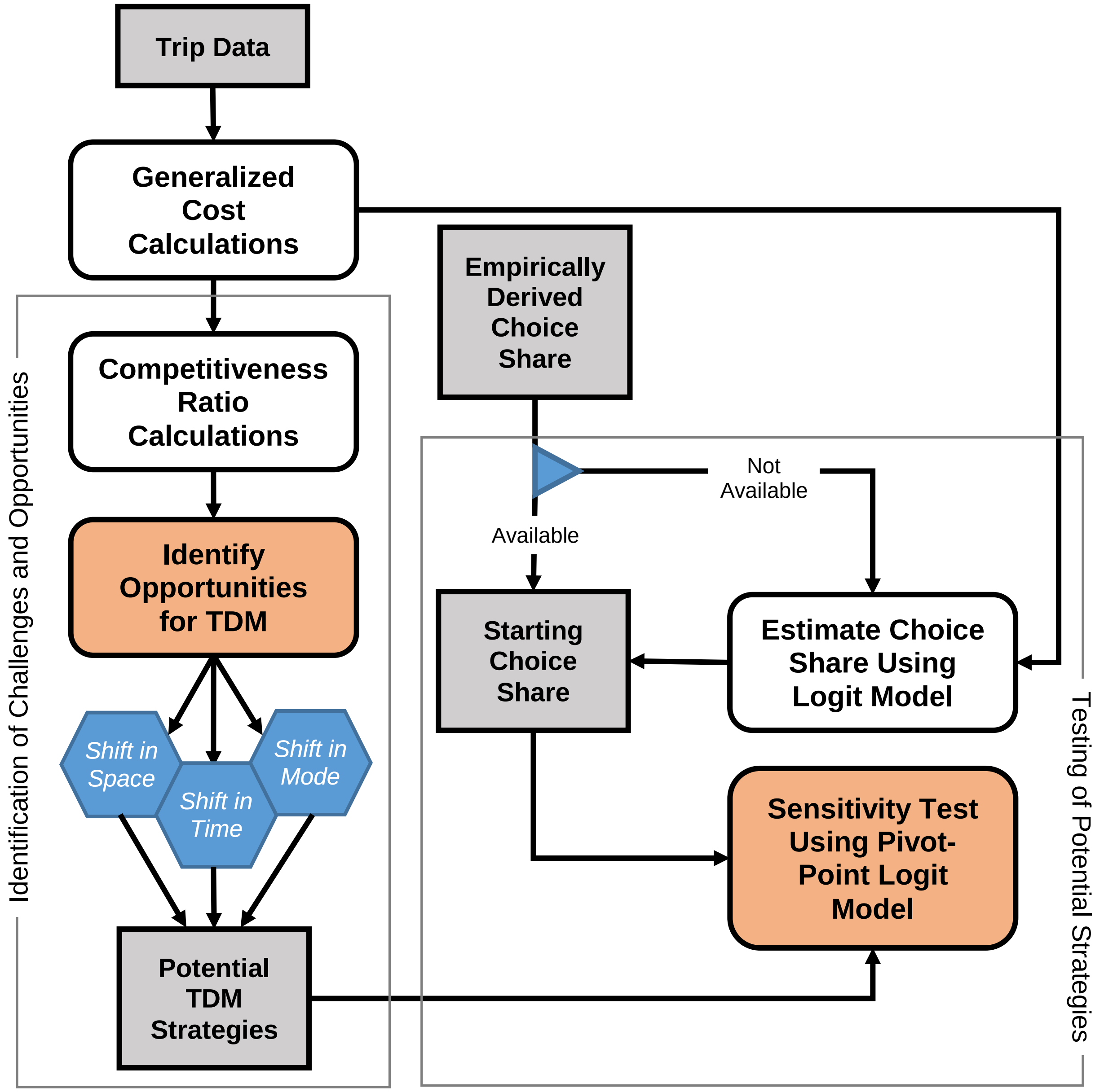


Figure 5 – Overview of Model Framework

The second module is used to test the potential of strategies to shift travel demand. The analysis begins by establishing the choice share across the alternatives available to a hypothetical traveller, either drawing from empirical data or by estimation through a logit model, using the generalized costs calculated at the beginning of the model. Here, choice share refers to the probability of a traveller to make a given choice across options in space, time, and mode, with the full suite of options available bounded by a specified choice set. Once the starting choice shares are established, TDM strategies selected from the first part of the model can be tested through a sensitivity analysis using a pivot-point logit model, also referred to as an incremental logit model. The benefit of a pivot-point logit model is that it simplifies the calculation of the estimated choice share by pivoting off of the existing choice share, relying just on the change in utility rather than the full utility value. The pivot-point logit model used in this analysis is based on previous models seen in literature such as the FHWA TDM Evaluation Model and COMMUTER Model discussed in section 2.4.1. The specifics of the model used in this application are described in further detail under section 3.7 of this thesis.

The modules within the model can be run sequentially as shown in Figure 5, or in isolation, depending on known information about the local context of the corridors and jurisdiction under analysis. In circumstances where target corridors and test TDM strategies have been pre-determined by other means, a user may begin their analysis in the second part of the model to test the demand shifting potential of the test TDM strategies without calculating the competitiveness ratios.

3.3 GENERALIZED COST CALCULATIONS

This analysis is focused on comparing the competitiveness of only two travel modes–auto and transit–during different times of day and along different paths of travel. The generalized cost of each travel alternative is quantified to represent its utility to a hypothetical user and is developed so that both monetary and non-monetary costs to a user are internalized. As such, generalized cost functions typically include variables that represent both travel time and out-of-pocket cost components. Travel time costs include all elements of time spent during travel, including the time spent in-vehicle, access to and egress from the vehicle, as well as any time spent waiting. Out-of-pocket costs include any cost elements that require an actual monetary transaction, such as fuel costs, transit fares, parking charges, and toll charges. In order to encapsulate all variables into a single generalized cost value, time related costs are typically converted into a monetary value by some value of time. As travellers tend to value the various cost elements differently, generalized cost functions also include coefficients which are used to convey the relative weight of each cost variable. Figure 6 below illustrates the conceptual formulation of a typical generalized cost function:

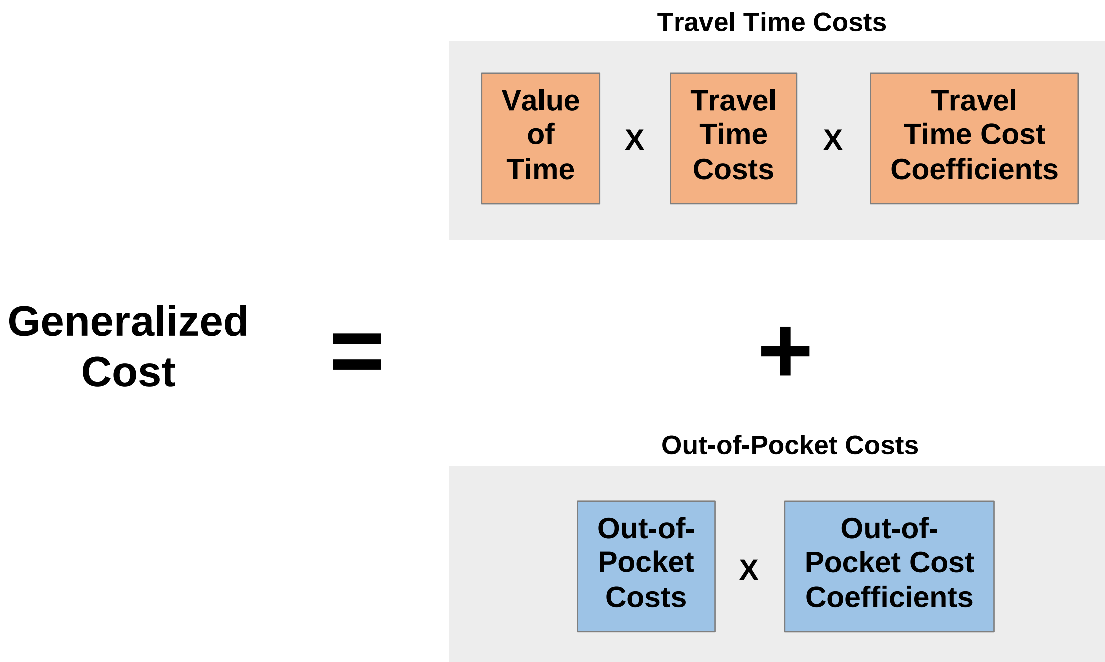


Figure 6 – Typical generalized cost composition

In this analysis, alternatives under two modes, auto and transit, are considered. To appropriately capture the distinct characteristics between the two modes, separate generalized cost functions have been developed. Table 2 outlines the key variables that are considered for each mode, grouped by travel time costs and out-of-pocket costs. To ensure all values are in common terms, all travel time costs are multiplied by a value of time (VOT) value to convert measures of time to a monetary value. As the focus of this model is to shift demand for one type of trip purpose, that being the journey to work, only one value of VOT is needed. The literature shows that VOT can vary depending on trip purpose (Calfee & Winston, 1998; Fallis, 2014; Lesley, 2009; Small, 2012). Further detail on how each of these variables are calculated can be found in Appendix A of this thesis.

Table 2 – Generalized cost variables for auto and transit

	Variable	Description	Generalized cost of Auto GC_{auto}	Generalized Cost of Transit $GC_{transit}$
Travel Time Costs	t_{access}	**Access Travel Time**	Negligible	Potentially for auto access to transit
Travel Time Costs	t_{wait}	**Wait Time**	No	Yes
Travel Time Costs	t_{IV}	**In-Vehicle Travel Time**	Yes	Yes
Travel Time Costs	t_{egress}	**Egress Travel Time**	Negligible	Yes
Out-of-Pocket Costs	C_{fuel}	**Fuel Cost**	Yes	Potentially for auto access to transit
Out-of-Pocket Costs	C_{toll}	**Toll Charge**	Yes	Potentially for auto access to transit
Out-of-Pocket Costs	$C_{parking}$	**Parking Charge**	Yes	Potentially for auto access to transit
Out-of-Pocket Costs	C_{fare}	**Fare Charge**	No	Yes

The generalized cost of travel by auto is calculated as a function of in-vehicle travel time and fuel costs, as well as toll charges and parking charges where applicable. In the model, the generalized cost of travel by auto is calculated using Equation 2.

Equation 2 – Generalized cost formula for auto

$$GC_{auto} = \frac{VOT}{60} \cdot (\beta_{IV}\, t_{IV}) + \beta_{fuel}\, C_{fuel} + \beta_{toll}\, C_{toll} + \beta_{parking}\, C_{parking}$$

Where:

t_{IV} = *in-vehicle travel time (min)*
C_{fuel} = *fuel cost ($)*
C_{toll} = *toll charge ($)*
$C_{parking}$ = *parking charge ($)*
VOT = Value of Time ($/hour)
β_{IV} = *coefficient for in-vehicle travel time*
β_{fuel} = *coefficient for fuel cost*
β_{toll} = *coefficient for toll charge*
$\beta_{parking}$ = *coefficient for parking charge*

The generalized cost of travel by transit features similar variables to the generalized cost for auto travel, with the addition of fare charge, and a number of other time variables. As shown in Equation 3, the cost of travel by transit includes variables for access travel time, transit wait time, and egress travel time in addition to the cost of in-vehicle travel time. Other variables included in the cost of travel by auto, such as the cost of fuel, tolls, and parking, have also been included in the cost of travel by transit calculation as the access leg of transit trips can be made using a variety of modes, including auto.

Equation 3 – Generalized cost formula for transit

$$GC_{transit} = \frac{VOT}{60} \cdot \left(\beta_{access}\, t_{access} + \beta_{IV}\, t_{IV} + \beta_{wait}\, t_{wait} + \beta_{egress}\, t_{egress}\right) + \beta_{fuel}\, C_{fuel} + \beta_{toll}\, C_{toll} + \beta_{parking}\, C_{parking} + \beta_{fare}\, C_{fare}$$

Where:

t_{access} = *access travel time (min)*
t_{IV} = *in-vehicle travel time (min)*
t_{wait} = *wait time (min)*
t_{egress} = *egress travel time (min)*
C_{fuel} = *fuel cost ($)*
C_{toll} = *toll charge ($)*
$C_{parking}$ = *parking charge ($)*
C_{fare} = *fare charge ($)*
VOT = Value of Time ($/hour)

β_{access} = *coefficient for access travel time*
β_{IV} = *coefficient for in-vehicle travel time*
β_{wait} = *coefficient for wait time*
β_{egress} = *coefficient for egress travel time*
β_{fuel} = *coefficient for fuel cost*
β_{toll} = *coefficient for toll charge*
$\beta_{parking}$ = *coefficient for parking charge*
β_{fare} = *coefficient for fare charge*

Both equations 2 and 3 build on the generalized cost formulations used by Taylor, Nozick, & Meyburg (1997), Jung (2017), and within the COMMUTER model (United States Environmental Protection Agency, 2000b). Coefficients corresponding to each of the variables provide a mechanism for adjusting the relative weighting of cost components to better reflect how each component is perceived by travellers. Under usual circumstances, these coefficients would be calibrated to the specific context by applying multinomial logistic regression analysis to a set of observed local travel behaviour data. For demonstration purposes, the model used in this research adopts values sourced from the literature and similar models. Further information on the coefficient values used within this model can be found in section A.10 of Appendix A.

Central to the calculations of generalized cost are the trip data used as input. The data employed in this analysis, specifically travel routes, travel times, and travel distances, come mainly from crowdsourced travel data taken from web-mapping applications such as Google Maps. These data are supplemented with other cost information, such as toll, rates, fares, and parking costs, which have been obtained from other online sources. Although data from conventional travel surveys or modeled travel times and travel distances could also be used, crowdsourced travel data have the benefit of being derived from a large sample, and having a high degree of time granularity. As data are collected from travellers in the transportation network during all hours of the day, and over an extended period of time, data are available to represent travel anywhere in the network at virtually all times. The resulting data show obvious time-of-day and even day-of-week variations in travel time across the network that are atypical to conventional data sources. This attribute allows for easier comparison of alternatives across the time, without the need to worry about time periods for which data have not been collected. The closest approximation to this level of time granularity in data comes from 24-hour traffic counts, which are typically conducted on a road by road basis, and would come at a prohibitive cost if conducted on a regional scale. Other data collection methods which may cover a larger geography are often limited in temporal scale. While other location enabled survey methods, such as GPS travel surveys, either by dedicated device or smartphone, may provide comparable temporal coverage of daily travel patterns, the sample size and reach are usually much more limited. Further details on how data were collected and used for this analysis has been included in section 4 of this thesis.

3.4 COMPETITIVENESS RATIO CALCULATIONS

The first part of the analysis is aimed at highlighting the challenges experienced within each of the target corridors in order to better identify opportunities to apply potential TDM strategies. With generalized costs calculated for each of the alternatives, a comparative analysis can be conducted on the basis of competitiveness ratios between the discrete options. This part of the analysis identifies opportunities in three dimensions: opportunities to shift travel in space; opportunities to shift travel in time; and opportunities shift travel by mode.

When a traveller makes a decision about their travel, they are presented with a suite of options, termed in this thesis as a choice set. Expanding on the concept of mode choice, which represents the modal options available to a traveller, the concept of choice set encapsulates all the options available across space, time, and mode. Considering this from the perspective of a traveller, their choice set is anchored around the alternative that they currently use or is most likely to use, and includes all other alternatives available to them for the intended trip. Figure 7 illustrates the choice set concept from the traveller's perspective.

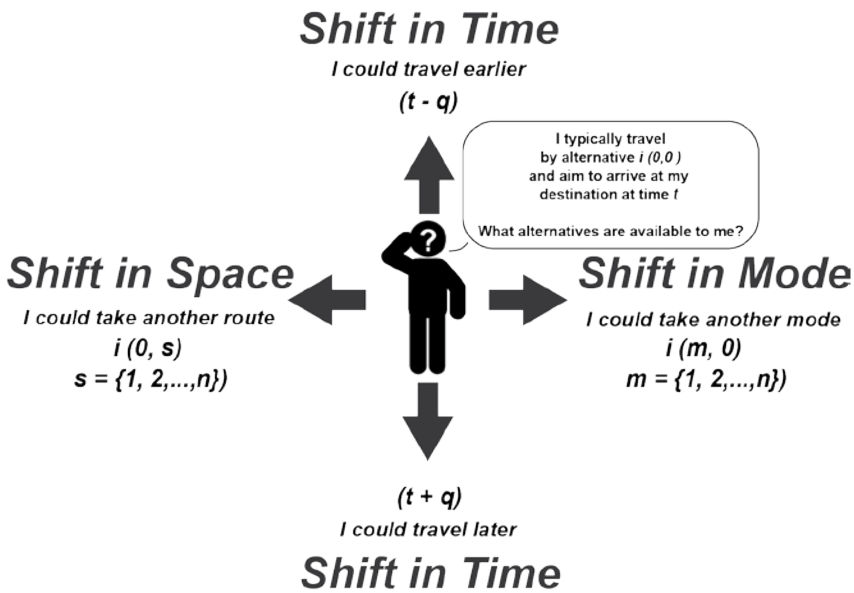


Figure 7 – Traveller consideration of alternatives in space, time, and mode

The traveller typically travels using alternative $i\ (m, s)$, where the mode option (m) and space option (s) both equal 0 (i.e. ($m = 0$) and ($s = 0$)), with the aim of arriving at their intended destination by time t. In considering changes to their usual travel behaviour, the traveller has several options available. The traveller could consider taking an alternate route by shifting in space (s) to options other than $s = 0$, or try taking an alternate mode by shifting in mode (m) to options other than $m = 0$. Likewise, the traveller could also consider traveling at a different time, by shifting their intended time of arrival to an earlier time, $t – q$, or to a later time, $t + q$, where q is the number of hours away from time t. Section 3.6 further elaborates how the choice set is defined and constrained within this thesis.

When calculating the competitiveness ratios, the same analysis method is used to explore both opportunities to shift travel in space and by mode, while an adapted method is used to explore opportunities to shift travel in time. In the case of shifts in space and by mode, a base alternative across space and mode is selected to begin the analysis. Since all corridors of travel have the option for auto travel by local roads, this is used as the default, or base option. This base option is conceptually separate from the typical travel alternative of the user described in Figure 7, but is similarly selected out of the set of space and mode options, i. Where contextual information about the corridor under analysis is available, such as known congestion or reliability issues associated with a specific highway facility, such alternative may be chosen to serve as the basis for comparison in order to identify competing alternatives that may help to remedy the situation. Equation 4 defines the calculation method for the competitiveness ratio across space and mode at time t.

Equation 4 – Competitiveness Ratio (space and mode)

$$Competitiveness\ Ratio\ (space/mode)_{j,t} = \frac{GC_{j,t}}{GC_{i,base,t}}$$

Where:

$i = Index\ of\ all\ space\ (s)\ and\ mode(m)\ alternatives, including\ j$
$j = Index\ of\ alternative\ under\ analysis$
$t = Time\ of\ day\ under\ analysis$
$GC_{j,t} = Generalized\ cost\ of\ alternative\ j\ at\ time\ t$
$GC_{i,base,t} = Generalized\ cost\ of\ alternative\ selected\ from\ i\ as\ the\ basis\ of comparison\ at\ time\ t$

The method used to explore opportunities to shift travel demand in time similarly relies on the calculation of a competitiveness ratio, but the comparison is conducted within an alternative, and not across different alternatives available. Across time, travel demand can be shifted to occur at an earlier or later time. As currently set up, the model compares the trip under analysis to travel by the same alternative arriving at the destination one hour preceding and following the time under analysis. Depending on the granularity of the trip data available as input, other time variance values may be used as well. Equation 5 defines the calculation method for the competitiveness ratio across time. It should be noted that travel at any time other than the intended time of travel should reflect a change in utility to account for the opportunity cost associated with either arriving early or late to the destination. For example, a traveller who arrives an hour early at their destination might waste an hour of their time waiting for the intended time of their activity, whereas a person who arrives an hour late may miss out on a portion of their intended activity, or face social scrutiny for their tardiness. This additional cost has not been captured in the calculations of the competitiveness ratios in order to provide a true comparison of the generalized cost across time. However, the additional cost for early and late arrivals is captured in module 2 of this analysis, discussed further on Page 49.

Equation 5 – Competitiveness Ratio (time)

$$Competitiveness\ Ratio\ (time)_{j,t} = \frac{GC_{j,t\pm q}}{GC_{j,t}}$$

Where:

$j = Index\ of\ alternative\ under\ analysis$
$t = Time\ of\ day\ under\ analysis$
$q = Time\ variance\ from\ time\ t$
$GC_{j,t} = Generalized\ cost\ of\ alternative\ j\ at\ time\ t$
$GC_{j,t\pm q} = Generalized\ cost\ of\ alternative\ j\ at\ time\ t\ plus\ or\ minus\ q\ hours$

3.5 IDENTIFY OPPORTUNITIES FOR TDM

TDM strategies that provide minor economic signals to travellers through incentives and disincentives work most effectively in situations where alternatives are competitively priced and feasible. For example, travellers in a corridor where transit takes only slightly longer in travel time than auto may be motivated to shift from auto travel to transit if transit fares are lowered, or if an additional charge is imposed on auto travel. In situations where alternatives are uncompetitive, such as where transit takes significantly longer, it would be difficult to generate shifts in behaviour, and other strategies, such as improved operations or infrastructure would have to be considered.

The value of the competitiveness ratio between alternatives provides indication of how comparable the alternatives are, with values closest to 1 representing the most comparable alternatives. Under this premise, it would be reasonable to assume that alternatives with a competitiveness ratio either slightly less than or greater than 1 would have the greatest potential for success when considering TDM strategies. In this analysis, competitiveness ratios have been grouped using the classifications shown in Table 3. Alternatives with competitiveness ratio values that fall within the 0 to 1 and 1 to 2 categories may be considered for further analysis of TDM potential. Alternatives that have a competitiveness ratio that is greater than 2 have a disutility that is more than twice that of the base alternative and are considered not competitive. In such instances, it is likely that more substantial solutions, such as infrastructure improvements and changes to service may be required to better align across alternatives. Depending on how the alternatives compare on the basis of competitiveness across space, time, and mode, test strategies can be selected for further testing to estimate their potential in shifting demand.

Table 3 – Interpretation of competitiveness ratio values

Value of Competitiveness Ratio	**Interpretation of Competitiveness Ratio**
0 to 1	Alternative is more or equally competitive to the base alternative
1 to 2	Alternative is equally or less competitive to the base alternative
2 +	Alternative is not competitive to the base alternative

3.6 ESTIMATE CHOICE SHARE USING LOGIT MODEL

The second part of the model is used to test the potential demand shifting capability of the test strategies chosen. The analysis used in this part of the model is based around the use of a logit model, similar to what is used in the mode share step of the traditional four-step travel demand model. This stage begins with input of a starting choice share for the alternatives, which provides the percentage of travellers that use each alternative for a particular corridor of travel. The use of choice share allows for simplification of the evaluation process as the pivot-point logit formulation requires only inputs of base shares and change in generalized cost rather than the full generalized cost of each alternative. Although empirical travel data are rarely disaggregated to the level of detail required to discern choice shares in space, time, and mode, the option to input empirically derived choice shares has been kept in case emerging methods of data collection enable this type of output. In the prevailing cases where empirical data about the existing choice share in the corridor of travel are not available, choice share can be estimated using a logit model, as shown in Equation 6. Note that generalized cost has been substituted into this equation in place of utility. As a result, all expressions of generalized cost are expressed as negative since any cost to a user is considered a negative disutility rather than a positive utility.

Equation 6 – Starting Choice Share

$$P(j) = \frac{e^{-GC_j}}{\sum_{l=1}^{n}(e^{-GC_l})}$$

Where:

$l = Index\ of\ all\ alternatives\ within\ the\ choice\ set\ across\ space, time, and\ mode, including\ j$
$j = Index\ of\ alternative\ under\ analysis$
$P(j) = Probability\ of\ a\ traveller\ choosing\ alternative\ j\ out\ of\ all\ alternatives\ in\ the\ choice\ set$
$GC_j = Generalized\ cost\ of\ alternative\ j$
$GC_l = Generalized\ cost\ of\ an\ alternative\ within\ the\ choice\ set\ l, including\ alternative\ j$

The choice set, *l*, can be considered as a scanning window that shifts across the dataset. Considering how a traveller might make a decision, the choices available to them include the full suite of alternatives available across space and mode at the time of analysis, as well as the alternatives available to them across time preceding and following the time of analysis. Returning to the concepts conveyed in Figure 7 in section 3.4, the options available to the hypothetical traveller can vary in two dimensions: across space and mode along values of *i (m,s)*; and across time along values of $t \pm q$. The choice set, which contains alternatives denoted by *l*, combines the options across both dimensions, and serves to constrain the range of discrete choices available for a hypothetical traveller to choose from against their default choice *i (0,0)* across space (s), mode (*m*), and intended time of arrival (*t*). Figure 8 provides a conceptual illustration of how the scanning window works to encapsulate a single choice set that considers the full suite of alternatives, as well as the opportunity for travel across time in the hour preceding and following the time of analysis.

With a total of 5 options across space and mode, and 2 options across time, the choice sets shown in Figure 8 each hold 7 alternatives of *l*. In example 1 of Figure 8, the default mode and space choice of *i(0,0)* is set to 'Auto – Local', with an arrival time *t* of 8:00 AM. Therefore, the choice set for this default choice spans the range of alternatives across space and mode about time *t* at 8:00 AM, with the addition of alternatives for 'Auto – Local' across time from *t – 1* to *t + 1*, 7:00 AM to 9:00 AM. In the second example, the scanning window has shifted to a default choice of 'Auto – Highway with Tolls' at 5:00 PM. The resulting choice set for this frame of the scanning window spans all the space and mode alternatives with an arrival time of 5:00 PM, as well as the 'Auto – Highway with Tolls' alternatives at 4:00 PM and 6:00 PM.

Figure 8 – Sample Scanning Windows

(1) Scanning Window Sample 1 – Default Choice of Auto – Local with Arrival at 8:00 AM

			Space & Mode				
	i(m, s) / ***t ± q***		***m = 0 s = 0***	***m = 0 s = 1***	***m = 0 s = 2***	***m = 1 s = 0***	***m = 1 s = 1***
			Auto Local	**Auto** Highway (no tolls)	**Auto** Highway with Tolls	**Transit** Local	**Transit** Regional
Arrival Time	6:00 AM	*t - 2*	*i(0,0); t – 2*	*i(0,1); t – 2*	*i(0,2); t – 2*	*i(1,0); t – 2*	*i(1,1); t – 2*
	7:00 AM	*t - 1*	***i(0,0); t – 1; l = 2***	*i(0,1); t - 1*	*i(0,2); t - 1*	*i(1,0); t - 1*	*i(1,1); t - 1*
	8:00 AM	*t*	***i(0,0); t; l = 1***	***i(0,1); t; l = 4***	***i(0,2); t; l = 5***	***i(1,0); t ; l = 6***	***i(1,1); t; l = 7***
	9:00 AM	*t + 1*	***i(0,0); t + 1; l = 3***	*i(0,1); t +1*	*i(0,2); t + 1*	*i(1,0); t + 1*	*i(1,1); t + 1*
	10:00 AM	*t +2*	*i(0,0); t + 2*	*i(0,1); t +2*	*i(0,2); t + 2*	*i(1,0); t + 2*	*i(1,1); t + 2*

Choice Set				
l	**m, s, *t ± q***	**m**	**S**	***t ± q***
1	0, 0, t ± 0	Auto	Local	8:00 AM
2	0, 0, t - 1	Auto	Local	7:00 AM
3	0, 0, t + 1	Auto	Local	9:00 AM
4	0, 1, t ± 0	Auto	Highway (no tolls)	8:00 AM
5	0, 2, t ± 0	Auto	Highway (with tolls)	8:00 AM
6	1, 0, t ± 0	Transit	Local	8:00 AM
7	1, 1, t ± 0	Transit	Regional	8:00 AM

(2) Scanning Window Sample 2 – Default Choice of Auto – Highway with Tolls with arrival at 5:00 PM

			Space & Mode				
	i(m, s)		***m* = 0** ***s* = 2**	***m* = 0** ***s* = 1**	***m* = 0** ***s* = 0**	***m* = 1** ***s* =0**	***m* = 1** ***s* = 1**
	t* ± *q		**Auto** Local	**Auto** Highway (no tolls)	**Auto** Highway with Tolls	**Transit** Local	**Transit** Regional
Arrival Time	2:00 PM	*t - 3*	*i(0,2); t - 3*	*i(0,1); t - 3*	*i(0,0); t - 3*	*i(1,0); t - 3*	*i(1,1); t - 3*
	3:00 PM	*t - 2*	*i(0,2); t – 2*	*i(0,1); t – 2*	*i(0,0); t – 2*	*i(1,0); t – 2*	*i(1,1); t – 2*
	4:00 PM	*t - 1*	*i(0,2); t – 1*	*i(0,1); t – 1*	***i(0,0); t – 1;l = 2***	*i(0,2); t – 1*	*i(0,1); t – 1*
	5:00 PM	*t*	***i(0,2); t; l = 5***	***i(0,1); t; l = 4***	***i(0,0); t; l = 1***	***i(1,0); t;l = 6***	***i(1,1); t; l = 7***
	6:00 PM	*t + 1*	*i(0,2); t + 1*	*i(0,1); t + 1*	***i(0,0); t + 1;l = 3***	*i(0,2); t + 1*	*i(0,1); t + 1*

Choice Set				
l	**m, s, *t* ± *q***	**m**	**S**	***t* ± *q***
1	0, 0, t ± 0	Auto	Highway (with tolls)	5:00 PM
2	0, 0, t - 1	Auto	Highway (with tolls)	4:00 PM
3	0, 0, t + 1	Auto	Highway (with tolls)	6:00 PM
4	0, 1, t ± 0	Auto	Highway (no tolls)	5:00 PM
5	0, 2, t ± 0	Auto	Local	5:00 PM
6	1, 0, t ± 0	Transit	Local	5:00 PM
7	1, 1, t ± 0	Transit	Regional	5:00 PM

As the scanning window shifts over different parts of the data set, alternatives at different times of day may be captured into the analysis of different choice sets, depending on the default choice used to anchor the analysis. This means that the choice share of an alternative at a given time of day can change as a function of the other choices that are included within the choice set that it is a part of. This constrained view of the options available is intended to represent more closely the choices that a traveller may feasibly consider as alternatives to their usual travel. The notion behind this limited choice set is in line with the idea that travellers are boundedly rational, meaning that a traveller's ability to choose among options is limited by their knowledge of the available options, which in most cases is limited and imperfect (van Essen, Thomas, van Berkum, & Chorus, 2016).

In considering shifts in travel across time, as in the case of alternatives at time $t \pm q;\ q \neq 0$, the generalized cost of travel should be considered more onerous than the hypothetical traveller's default choice as it deviates from the traveller's wish to arrive at their destination at exactly time *t*. A number of researchers have postulated that such deviations from a traveller's intended travel choice would result in some increase to the level of disutility experienced, and most agree that for trips to work or some other scheduled appointment that is bound by a strict schedule, late arrivals have a greater negative impact than early arrivals (Ben-Akiva, De Palma, & Isam, 1991; Chow & Recker, 2012; Lam & Small, 2001; Noland & Polak, 2002; Nour et al., 2010; Small, 1982; Small & Verhoef, 2007).

This model adopts the early and late arrival penalties developed by Small through an empirical study. Small suggests that the marginal rate of substitution for early arrivals is 0.61 per minute, and 2.4 per minute for late arrivals (1982). However, his research also notes that in the case of most scheduled events, travellers are often afforded a "margin of safety", which is an allowable amount of late arrival time that does not incur a cost greater than normal travel time (Small, 1982). An early arrival penalty is applied to alternatives where $q < 0$, while the late arrival penalty is applied to alternatives where $q > 0$. Since the penalty is an additional cost to a travellers' disutility, it can be simply added on top of already calculated generalized cost values for each corresponding alternative. Equation 7and 8, which are derived from the research of Small (1982), provide the mathematical basis for these time penalties.

Equation 7 – Cost of early arrival

$$EARLY = \frac{VOT}{60} \cdot (\beta_{early}\ t_{early}\ )$$

Where:

$EARLY = Early\ arrival\ penalty\ (\$)$
$VOT = Value\ of\ Time\ (\$/hour)$
$\beta_{early} = Coefficient\ for\ early\ arrival\ time = 0.61$
$t_{early} = Early\ arrival\ time\ (min) = Intended\ arrival\ time - Actual\ arrival\ time = t - q\ ; q < 0$

Equation 8 – Cost of late arrival

$$LATE = \frac{VOT}{60} \cdot (5.5 + \beta_{late}\, t_{late}\ )$$

Where:

$LATE = Late\ arrival\ penalty\ (\$)$
$VOT = Value\ of\ Time\ (\$/hour)$
$\beta_{late} = Coefficient\ for\ late\ arrival\ time = 2.4$
$t_{late} = Late\ arrival\ time\ (min) = Actual\ arrival\ time -\ Intended\ arrival\ time = q - t\ ; q > 0$

3.7 SENSITIVITY TEST USING PIVOT-POINT LOGIT MODEL

The last step in the model is used to estimate the demand shifting capabilities of proposed TDM strategies. Extending the use of the logit model, this part of the analysis employs a pivot-point, or incremental logit model, which estimates changes in choice shares on the basis of the incremental changes to the generalized cost or utility of each alternative. Equation 9 provides the formulation for the pivot-point logit model used, adapted from research by Taylor et al. (1997) and the COMMUTER model (United States Environmental Protection Agency, 2000b). Similar to the logit model shown in Equation 1, the term for generalized cost has been used in place of utility. As any increase in generalized cost represents a decrease in utility for the user, all changes that result in an increase in cost, such as the addition of tolls or parking charges, would result in a negative generalized cost value, or an added disutility. As such, changes to generalized cost are, by default, captured in negative terms. Decreases to the generalized cost through strategies such as decreased transit fare costs or shortened travel time would, by the same logic, result in a positive gain in generalized cost. Similar to the procedures used for estimating the starting choice share described in section 3.6, the choice set is defined by a scanning window, which constrains the alternatives available, particularly in the time dimension.

Equation 9 – Pivot-Point Logit Model

$$P'^{(j)} = \frac{P(j) \times e^{-\Delta GC_j}}{\sum_{i=1}^{n}(P(i) \times e^{-\Delta GC_i})}$$

Where:

$i = Index\ of\ all\ alternatives\ within\ the\ choice\ set, including\ j$
$j = Index\ of\ alternative\ under\ analysis$
$P(j) = Starting\ choice\ share\ of\ j$
$P'(j) = New\ choice\ share\ of\ j$
$\Delta GC_j = \ Change\ in\ generalized\ cost\ of\ alternative$
$P(i) = Starting\ choice\ share\ of\ any\ alternative\ within\ the\ choice\ set, including\ alternative\ j$
$\Delta GC_i = \ Change\ in\ generalized\ of\ any\ alternative\ within\ the\ choice\ set, including\ alternative\ j$

3.8 CHAPTER SUMMARY

This chapter presents a model framework for identifying opportunities in TDM and evaluating the performance of specific TDM strategies at a corridor level. The first module, which is aimed at identifying opportunities for TDM, uses competitiveness ratios to quantify how various travel alternatives compare on the basis of generalized cost. The second module, evaluates the performance of test strategies using a pivot-point logit model, which adjusts the expected choice shares across alternative options in space, time, and mode as a function of changes to the generalized cost of the alternatives.

Fundamental to this model is the input of trip data, which is used to inform the calculations of generalized cost for the various alternatives. While conventional and modelled sources of data may also be used, the methods have been formulated with the use of crowdsourced travel data in mind. The benefit of using crowdsourced data sources, such as Google Maps, is that the data is relatively easy to access, is based on a large sample, and thus, has a wide geographic and temporal coverage. Whereas other data sources may have high geographic coverage but only during peak periods, or focused geography over a wide temporal coverage, crowdsourced travel data is able to satisfy both. Further detail on how this data has been collected for the purpose of this thesis is covered in chapter 4.

4.0 APPLICATION

The model structure described in the previous section builds on evaluation techniques uncovered in the literature to offer a framework for identifying and evaluating potential opportunities for TDM strategy application. In this section, the model framework is applied to a set of corridors, not only to seek out opportunities for TDM application, but also to test the usability and accuracy of the model against known conditions. The following sections describe the process taken to apply the analysis techniques in three parts: data collection; identification of challenges and opportunities; and evaluation of potential strategies. Sample outputs from the analysis are presented, and a number of key observations are discussed.

4.1 OVERVIEW

Similar to other regions across North America, the Greater Toronto and Hamilton Area (GTHA) experiences immense challenges relating to congestion and auto-dependency. Historically oriented around the City of Toronto, the public transit infrastructure in the region has been challenged to keep pace with the restructuring of the region to a more polycentric form. Although a significant program of new infrastructure has been planned to meet the region's evolving needs, it is still to be seen whether these projects will be effective in addressing the mobility challenges faced in this region.

In this section, the model framework described in section 3.0 is applied to a set of six test corridors in the GTHA. The six corridors are bound by four origin-destination Mobility Hubs, which are areas in the region that have been designated for growth and improved transit connectivity. Figure 9 maps out the system of Mobility Hubs that have been designated across the region. As many of the Mobility Hubs in the region are located in suburban areas where auto-dependency remains high, a primary goal is to motivate shifts in behaviour toward lower impact modes such as transit. The model is used to screen through the six corridors of analysis to identify potential opportunities where TDM application may be viable, and to evaluate the impact of several test TDM strategies on travel behaviours within these corridors.

As one of the main objectives of this thesis is to explore the applicability of Google Maps travel time data in transportation analyses such as those employed in this model, the model application process begins with an in depth account of the Google Maps data collection process in section 4.3. Although more automated methods of data collection are available, such as through the Google Maps APIs, the data used in this research were collected manually to ensure that all issues and challenges would be captured. Sections 4.4 and 4.5 detail the model process taken to apply the two modules of the model and documents some of the major findings from the analysis.

4.2 STUDY LOCATION

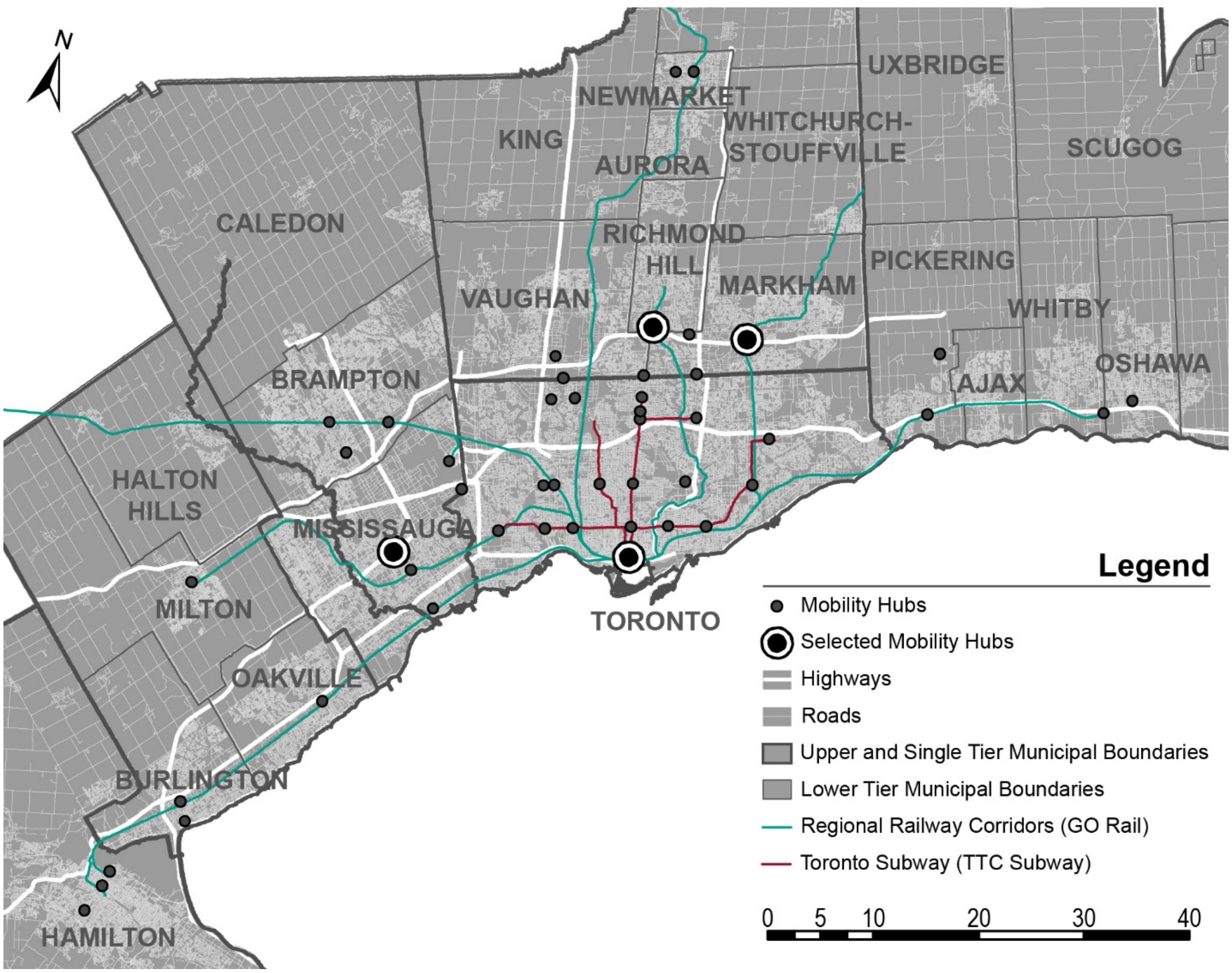


Figure 9 – Map of Study Location: Greater Toronto and Hamilton Area

The GTHA represents the largest contiguous urban area in Canada. Since the early 2000s, the GTHA has been a major focal point of provincial and regional planning efforts due to its rapid population growth. The area is made up of six upper and single-tier municipalities, including the City of Toronto, which is the country's most populous city. Upper tier municipalities are also referred to as regional municipalities as they govern a jurisdiction of multiple smaller local municipalities. The two single-tier municipalities, the City of Toronto and City of Hamilton, operate on a similar level to the upper tier municipalities, but do not have any other local municipal governments under their jurisdiction. While the City of Toronto has maintained a central role in the region throughout much of history, efforts to address population growth and resulting traffic congestion have contributed to an increasingly polycentric regional form. Metro Toronto's 1992 Official Plan was one of the first to plans to propose this structure for the region. Since then, other plans have emerged, the most recent iteration being the Urban Growth Centre and Mobility Hub concepts developed by the Province of Ontario through its "Places to Grow-Growth Plan for the Greater Golden Horseshoe" and Metrolinx through the "Big Move Regional Transportation Plan". The latest plans have also been accompanied with unprecedented levels of capital spending on new transportation infrastructure projects across the region.

The analysis has been applied to a selection of corridors that connect four centres within the GTHA that have been co-designated both as Urban Growth Centres and Mobility Hubs. The Mobility Hubs, as they are named in the "Big Move Regional Transportation Plan" are: Union; Mississauga City Centre; Richmond Hill-Langstaff Gateway; and Markham Centre. Representative point locations for each of the four Mobility Hubs have been used as origin and destination locations in this analysis.

The nodes in this study were selected for their proximity to major highway facilities within the region, and existing transit service connectivity to the region. As designated Mobility Hubs, each node connects a number of local and regional transit services, and contains a GO Transit rail or bus station. The four selected Mobility Hubs are also connected by a network of provincial and municipal highways, namely the 400-series highways (400, 401, 403, 404, 409, 410, 427,), the Don Valley Parkway (DVP), the Gardiner

Expressway (GEX), the Queen Elizabeth Way (QEW), and the 407 Express Toll Route (ETR). A more detailed map of the selected Mobility Hubs is shown in Figure 10. The six corridors have been analyzed bi-directionally across different times of day, and for a number of different space and mode alternatives which are described further in section 4.3.

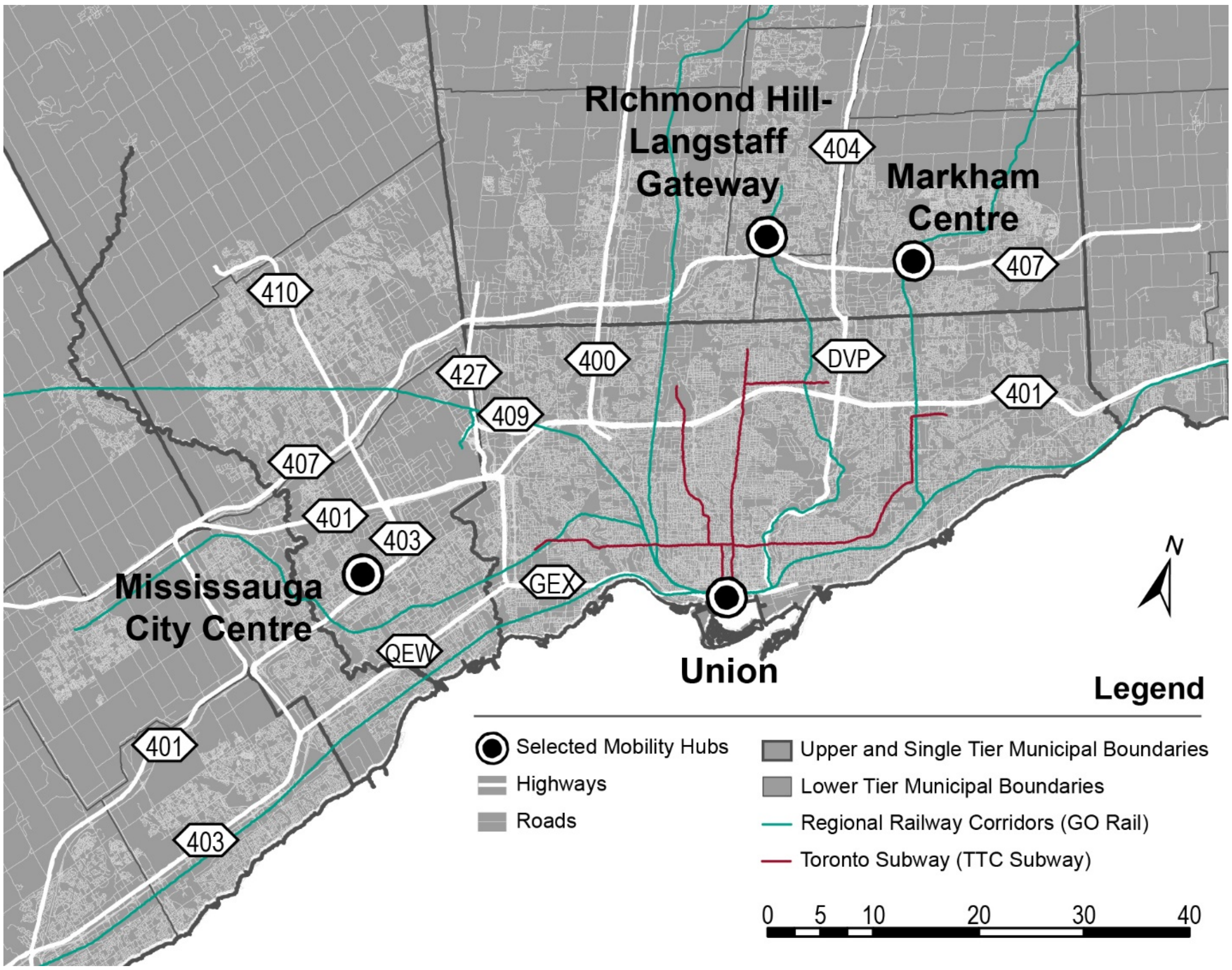


Figure 10 – Selected Origin-Destination Mobility Hub Locations

With the exception of the Union Mobility Hub, located at the very core of Downtown Toronto, all the selected mobility hubs are situated in suburban municipalities where auto use remains high. Most employment areas in these suburban municipalities are characterized by large swaths of parking that contribute to the convenience of travelling by personal automobile. Significant emphasis has been paid over the last decade to decreasing auto-dependence across the region, and the suburban municipalities will need substantial changes in travel behaviour to make this happen.

While there is a significant amount of new transit infrastructure under construction and in implementation, it remains to be seen whether these investments will achieve the intended impacts. For a number of Mobility Hubs in the region, including the Markham Centre and Richmond Hill Centre-Langstaff Gateway, the implementation of a Regional Express Rail (RER) network is expected to bring about transformational change. As it stands, the majority of regional rail corridors in the region operate only in the peak direction of travel to serve a commuter market anchored on the city of Toronto. The RER program aims to convert these corridors to enable all day bi-directional travel so that Mobility Hubs across the region can become more prominent activity centres in their own right rather than access points into Toronto's Downtown Core. Metrolinx's capital program also includes a number of light rail transit (LRT) and bus rapid transit (BRT) projects, including the Hurontario-Main LRT in Mississauga, which would serve to connect the Mississauga City Centre Mobility Hub to the regional higher-order transit network. Table 4 provides an overview of the mode shares for each of the municipalities or areas in which the Mobility Hubs reside, reported through the 2011 Transportation Tomorrow Survey (Data Management Group, 2011).

Table 4 – 2011 Mode Shares for Municipalities of Selected Mobility Hubs

	Trips Made by Residents						Trips Made to Municipality/Area					
	Driver	**Passenger**	**Transit**	**GO Train**	**Walk & Cycle**	**Other**	**Driver**	**Passenger**	**Transit**	**GO Train**	**Walk & Cycle**	**Other**
Across 24 hours												
Toronto (Downtown Core)[1] *Union*	29%	8%	32%	0%	28%	3%	27%	7%	39%	10%	15%	2%
Markham *Markham Centre*	71%	15%	4%	0%	7%	3%	70%	18%	5%	1%	4%	1%
Richmond Hill *Richmond Hill Centre-Langstaff Gateway*	68%	17%	7%	3%	3%	2%	70%	17%	6%	2%	3%	2%
Mississauga *Mississauga City Centre*	65%	17%	8%	3%	5%	2%	68%	17%	7%	1%	5%	2%
During morning peak period from 6 AM to 9 AM												
Toronto (Downtown Core)[2] *Union*	26%	5%	36%	0%	31%	2%	22%	5%	42%	21%	9%	1%
Markham *Markham Centre*	67%	18%	7%	3%	4%	1%	71%	15%	4%	0%	7%	3%
Richmond Hill *Richmond Hill Centre-Langstaff Gateway*	64%	14%	8%	6%	4%	4%	69%	16%	5%	-	6%	4%
Mississauga *Mississauga City Centre*	62%	15%	8%	5%	7%	3%	70%	14%	5%	0%	7%	4%

[1] Data for Planning District 1 (PD1) used for Toronto (Downtown Core)
[2] Data for Planning District 1 (PD1) used for Toronto (Downtown Core)

4.3 DATA COLLECTION

One of the core objectives of this research is to explore the possibility of using crowdsourced data, namely Google Maps data, to inform transportation planning functions such as the calculation of generalized costs. Traveller information systems such as Google Maps are typically used to provide travellers with directions and information about their travel on various modes. With recent developments in technological capability, there has been a growing trend towards incorporating historic and real-time data into the travel time predictions and route recommendations generated. As such, data that are harvested from traveller information systems are possibly more accurate to actual travel conditions than the model estimated travel times that are typically used (F. Wang & Xu, 2011).

In this thesis, Google Maps data are used to inform the analysis in two ways. The first is to provide recommendation for the optimal routing between origins and destinations for each of the alternatives. The second is to inform the travel time and travel distance components of the generalized cost calculations for each of the respective routes of travel between origins and destinations, which in this case are the Mobility Hubs. These data are supplemented by other sources, such as toll and parking fee schedules, transit service schedules, fuel cost records, and values from literature to provide a comprehensive perspective of all costs incurred by travellers.

Although Google has made a number of Application Programming Interfaces (APIs) available for developers to easily access the available data, the data collection in this research has been conducted using a manual approach so that any issues associated with the data collection can be properly documented. A thorough account of the challenges and limitations associated with this data collection process is included in section 5 of this thesis. As the alternatives put forward are intended to be indicative of the conditions for a general flow of travel within a corridor, some of the travel time components have been generalized in order to not overly disadvantage some alternatives against others simply because of assumed starting locations, or service schedules. For example, late and early arrivals that have come about as a result of mismatch between time t and the scheduled arrivals of transit trips at the destination are disregarded as travellers would presumably be able to make some adjustment to their intended time of arrival if their usual travel pattern is bound by the transit schedule. Other aspects of travel, such as access time and egress time, which could vary from traveller to traveller have been generalized using assumed values which are documented in Appendix A. This section details some of the rules and procedures used, as well as some of the observations made during the data collection process.

4.3.1 *Set-Up and Route Selection*

The first step in the data collection process involved the selection of routes to represent travel by different space and mode alternatives across the six analysis corridors. The generalized costs values required in the analysis are calculated according to the travel time and travel distances of the routes presented. Similar to many other web-mapping applications, the Google Maps web interface has the ability to provide optimal route recommendations based on origin and destination point locations and a number of select parameter inputs.

As the Mobility Hubs used as origin and destination locations in this analysis do not have official point locations, a set of representative coordinates were selected within the vicinity of each Mobility Hub. The representative point locations were selected based on the coordinates returned by Google Maps from a query of the transit station name that corresponds to each Mobility Hub. Table 5 lists the coordinates used to represent each of the Mobility Hubs. Travel between each of the Mobility Hubs makes up six analysis corridors. Considering travel going in both directions between the Mobility Hubs, a total of twelve streams of travel (two per corridor) were analyzed.

Table 5 – Origin-Destination Mobility Hub Locations

Mobility Hub	Transit Station Name	Latitude	Longitude
Union	Union Station	43.64522	-79.38047
Markham Centre	Unionville GO Station	43.85168	-79.31433
Richmond Hill-Langstaff Gateway	Richmond Hill Centre	43.84016	-79.42555
Mississauga City Centre	Square One GO Bus Terminal	43.59553	-79.64869

Once the origin-destination locations were established, parameters were selected to generate route recommendations that emulate the space and mode alternatives of interest. In this application of the analysis, five space-mode alternatives that represent auto and transit alternatives available in the region were considered. Across the auto related alternatives, three options across space were analyzed: 'Auto – Local'; 'Auto – Highway (No Tolls)'; and 'Auto – Highway (With Tolls)'. As for the transit related alternatives, two options that correspond to the types of transit service available in the region were evaluated: 'Transit – Local' and 'Transit – Regional'. Table 6 provides further detail on the alternatives analysed within the context of the study area.

Table 6 – Description of Mode – Space Alternatives

Mode - Space Alternative		Description
AUTO	Auto – Local	Auto alternative that uses only local roads. No highways and no toll roads (407 ETR)
	Auto – Highway (No Tolls)	Auto alternative that uses local roads and highways. No toll roads (407 ETR)
	Auto – Highway (With Tolls)	Auto alternative that uses local roads, highways and toll roads (407 ETR)
TRANSIT	Transit – Local	Transit alternative that relies strictly on the use of services by local transit operators, which includes all transit operators except for GO Transit
	Transit – Regional	Transit alternative that relies predominantly on the use of services by the regional transit operator, GO Transit, but potentially with some minor connections made using local services.

Route Selection - Auto Alternatives

Selection of input parameters for the auto alternatives was relatively straight-forward. For auto travel, the Google Maps web map interface provides a number of route options including facilities and services to avoid, and the distance units to use. For auto, the options are presented to avoid highways, tolls, and ferries. As water-based transport is not considered in this analysis, it is avoided under all alternatives by default. Table 7 shows the route parameters used in Google Maps when collecting data for each of the auto alternatives.

Table 7 – Route Selection Parameters for Auto Alternatives

Auto Alternative	**Highways**	**Tolls**
Auto – Local	avoid	avoid
Auto – Highway (No Tolls)	allow	avoid
Auto – Highway (With Tolls)	allow	allow

As traffic conditions tend to fluctuate by time of day, route recommendations presented can change. To maintain consistency throughout the analysis, one route was maintained for each mode-space alternative in the data collection. In situations where Google Maps offered more than one recommendation for a given auto alternative, the top recommendation provided for arrival by 9 AM was chosen and used consistently across the entire time scale.

Route Selection - Transit Alternatives

Data collection for transit alternatives proved to be more challenging as service availability varies by time of day, and route options provided by Google Maps do not align perfectly with the transit alternatives under analysis. The route options available for transit include route preferences of bus, subway, train, or tram/light rail, and a choice of routes that minimize walking, have fewer transfers, or is the 'best route' as defined by Google Maps. The main differentiation between the 'Transit – Local' and 'Transit – Regional' alternatives is the service operator and the type of service offering. 'Transit – Local' alternatives tend to travel shorter distances, have more frequent stops, and are operated by transit agencies in each of the individual municipalities, whereas 'Transit – Regional' services tend to travel longer distances, with fewer stops, and are operated by GO Transit, the regional transit agency which is under the jurisdiction of Metrolinx. As the regional services operated by GO Transit tend to charge a significantly higher base fare than the local transit operators, it is uncommon for travellers to use its services for short distances to connect to, from, or between local services. However, the route recommendations for the GTHA currently do not consider the fare cost associated with transit and in some instances provided route recommendations that combined regional "and local transit options in ways that would be unlikely for an actual traveller to take. As such, routes recommended by Google Maps required validation through the author's judgement. Figure 11 describes the algorithm used in choosing between route recommendations that arrive either before or after the intended time of arrival.

Figure 11 – Transit Route Selection Algorithm

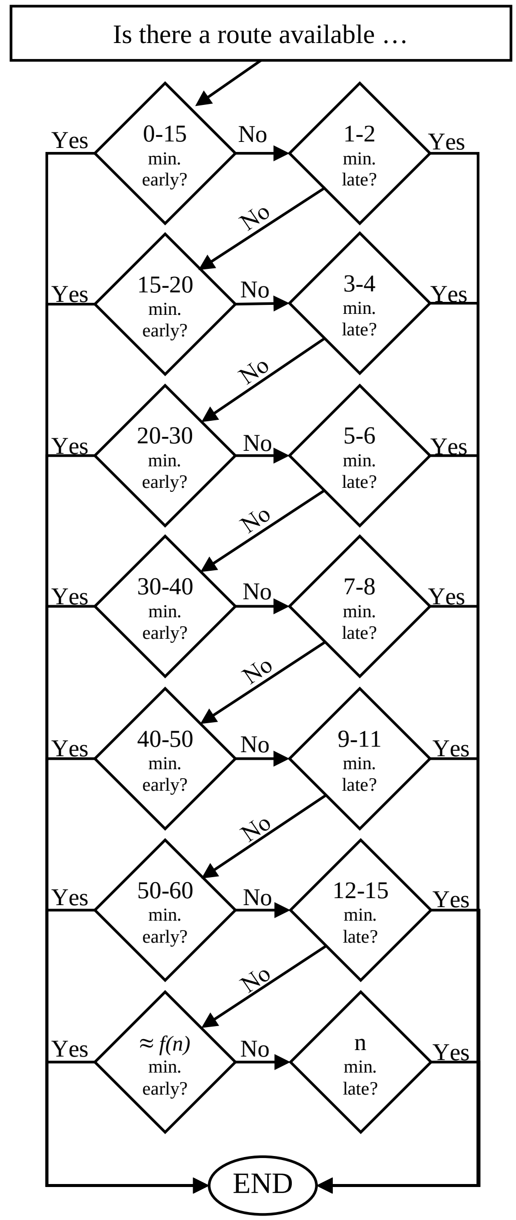
If LATE = EARLY, then:

$$t_{early} = \frac{(5.5 + \beta_{late}\, t_{late}\ )}{\beta_{early}}$$

Where:

$VOT = Value\ of\ Time\ (\$/hour)$
$\beta_{early} = Coefficient\ for\ early\ arrival\ time = 0.61$
$t_{early} = Early\ arrival\ time\ (min)$
$\beta_{late} = Coefficient\ for\ late\ arrival\ time = 2.4$
$t_{late} = Late\ arrival\ time\ (min)$

Late (min)	**Early (min)**	
1	12.95	**≈ 15**
2	16.89	
3	20.82	**≈ 20**
4	24.75	
5	28.69	**≈ 30**
6	32.62	
7	36.56	**≈ 40**
8	40.49	
9	44.43	**≈ 50**
10	48.36	
11	52.30	
12	56.23	**≈ 60**
13	60.16	
14	64.10	
15	68.03	
n	*f(n)*	**≈ *f(n)***



As a rule of thumb for choosing from multiple available route options, routes were compared using a basic search algorithm that simplifies the logic of the late and early arrival penalties discussed in section 3.6. As early arrivals are generally perceived to be less onerous than late arrivals, routes that arrive earlier are considered ahead of late arrivals for the equivalent or similar penalty cost. Figure 11 shows the sequence of decision points used for determining the appropriate transit route to select for analysis.

Google Maps also experienced difficulties identifying nearby transit services that are outside the immediate vicinity of the origin point location. This became a particular issue on trips that involved the Richmond Hill-Langstaff Gateway Mobility Hub, as the transit services for this location are spread across two distinct but connected areas. Although the two areas are separated by a railway corridor and station, the approximately 500m walk from one side to the other using the available pedestrian access bridge would have been much less onerous than the indirect route posited by Google Maps. In such instances, the routes were left out of the analysis. Further discussion on potential methods to mitigate such impacts in the future are provided in section 5.

4.3.2 *Time Granularity of Data Collected*

The time granularity of the data collected was limited by the frequency of available transit services. As transit service in some corridors of analysis had headways of just over an hour during off-peak periods, data could only be collected every two hours to prevent routes from being considered more than once. Unlike transit travel, auto travel is not tied to a schedule, and thus data could be collected at a much finer level of time granularity. In this analysis, auto travel times have been collected on an hourly basis from the period between 6 AM and 9 PM to align with the transit travel time data collected, but also provide an opportunity to investigate potential shifts in time across auto alternatives. Table 8 presents the alignment of analysis times between transit and auto modes.

Table 8 – Alignment of Data Points Available Between Transit and Auto Alternatives

		t_1		t_2		t_3		t_4		t_5		t_6		t_7		
Transit		7 AM		9 AM		11 AM		1 PM		3 PM		5 PM		7 PM		
Auto	6 AM	7 AM	8 AM	9 AM	10 AM	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM	8 PM	9 PM

4.3.3 Recording of Travel Times and Travel Distances

The Google Maps outputs were used in two ways: (1) to generate recommended route options, as described in section 4.3.1, and (2) to inform the calculation of generalized cost values for travel between the selected origin-destination Mobility Hubs. When directions for a route of travel between an origin and destination are requested through the Google Maps interface, a series of directions are returned, detailing the specific travel times and travel distances for each leg of the trip. These travel times and travel distances were used to inform the calculation of a number of variables in the generalized cost equation.

To obtain data results that are built on historic crowdsourced data, all queries were set to a day in the future so that Google Maps would generate predictive estimates rather than real-time information. For consistency, all queries to Google Maps were set to a Wednesday in the future to represent typical mid-week or weekday conditions. For each corridor of travel, data were collected in both directions, under each of the space and mode alternatives available, and across different times of day. Across the six corridors, a total of twelve directional flows were analyzed, leading to a total of sixty sets of queries once the alternatives have been accounted for, each with data collected for the entire time scale of the analysis. Where a mode-space alternative was unavailable, the results were omitted from the analysis. The following sections describe how the trip data was collected for each of the modal alternatives, auto and transit.

Auto Travel Data

For auto travel, the generalized cost formulation includes variables for in-vehicle travel time, fuel cost, toll charge, and parking charges. Travel time outputs from Google Maps for auto travel come as a number of different outputs: an optimistic estimate with the shortest total travel time; a worst case estimate with the longest total travel time; and an estimate of the typical travel time for each individual leg of the trip, which in many cases sums to a total travel time value that falls between the best and worst case scenarios. Observation of these outputs across the data collected finds that time-of-day variations in travel time are only captured in the optimistic and worst case scenarios, whereas the typical travel time estimates hidden in the leg specific details tend not to fluctuate. As in-vehicle travel time is the only one travel time variable in the auto generalized cost formulation, there is no need to disaggregate the travel time value into legs. Thus, only the total trip travel times were recorded for the auto alternatives. Both the optimistic and worst case travel time results were recorded, and an average of the two were used in the calculation of in-vehicle travel time.

The calculations for fuel cost and toll charge were informed by the travel distances returned by Google Maps for each of the travel routes. As a consistent route was chosen for each query, travel distances remained constant across the time scale of the data collection. Based on information reported by Statistics Canada, the average cost of fuel was determined to be 106.86¢ per litre. More information relating to the variables used in the fuel cost calculation, including the fuel efficiency, can be found in Appendix A, The total travel distance of the trip was summed from the individual leg distances reported in order to inform the calculation of the fuel cost variable. For the ‘Auto – Highway (With Tolls)’ alternative, travel distances returned by Google Maps were also used in the calculation of distance based toll charges for use of the tolled highway in the region, 407 ETR. The 407 ETR is priced according to distance, direction, time of day, and zone of travel. As Google Maps generally reports the entire length of travel on the tolled highway under one leg of travel, this became an issue for trips that used the 407 ETR across more than one toll zone. In such cases, an additional step of manual measurement of the travel distance had to be done so that the appropriate toll charge could be applied.

Lastly, parking charge is independent of the travel time or travel distance, so no part of the Google Maps data outputs were used in the calculation of this variable. Details on how the parking charge values were developed can be found in Appendix A, section A.7.

Transit Travel Data

The Google Maps outputs for transit reflect the scheduled route and travel times developed and uploaded by individual transit agencies. Although these data have not been crowdsourced from actual travellers and are not a direct reflection of the actual user travel times experienced, it has been assumed that the data closely approximates the expected conditions of travel by time of day. Due to the need for schedule adherence on the part of the transit agencies and service providers, the scheduled travel times should adequately reflect the typical travel conditions. It is anticipated that any changes to typical travel times by transit, for example, as a result of overall increased congestion or improved traffic conditions, would be captured through regular service adjustments conducted by the transit agencies.

For transit alternatives, the generalized cost formulation includes variables for access travel time, wait time, in-vehicle travel time, egress travel time, fare cost, and additional auto costs associated with access such as fuel cost, toll charge, and parking charge. The transit travel time outputs from Google Maps were used primarily to inform calculations of in-vehicle travel time. As many of the route recommendations posed by Google Maps included a number of trip legs that feature different transit services, travel times were captured individually for each leg of the trip as reported. Since the travel times are scheduled and not expected optimistic or worst case estimates, only one time value was presented for each leg.

Wait times were also calculated on the basis of information generated from the Google Maps outputs. However, despite there being wait times included in the trip specific outputs from Google Maps, the wait time calculations were conducted on the basis of transit time-table information. As the generalized costs are intended to broadly represent the travel conditions of certain periods of the day rather than a specific point in time, it was determined that the trip specific wait times would possibly either over-estimate the general amount of wait time required (i.e. if the trip recorded had just missed the connection), or under-estimate the wait time required (i.e. if the trip recorded was coincidentally timed in a way that minimized the wait time at the connection). To calculate transit wait times, headway information was gathered from transit agency schedules according to the information provided in the transit routings. In cases where headways were inconsistent, an average was taken over the two headways before and two headways after the intended trip. The formulation for the wait time calculation can be found in Appendix A, Equation 10.

Other cost components, such as access time, egress time, and fares, which are less variable across specific trips, have been provided in Appendix A of this thesis. Assumptions around access and egress were determined on the basis of station access figures reported by Metrolinx. Consequently, fuel costs, parking charges, and toll charges related to access were calculated on the basis of these assumptions. Transit fare information was collected from the various transit agencies along with rules around transfers between service providers and special routes.

4.4 MODULE 1 - IDENTIFICATION OF CHALLENGES AND OPPORTUNITIES

As described in the methods section, the first module of the TDM evaluation model takes inputs of trip data (travel times and travel costs) to identify challenges and opportunities across space, time, and mode where TDM strategies may be applied to help promote shifts in travel behaviour. Generalized costs were calculated for each trip record captured in the data collection process and used to generate competitiveness ratios.

Calculation of the competitiveness ratios followed the methods set out in section 3.4. As the ‘Auto – Local’ alternative is one that is consistently available across all origin-destination pairs, it has been chosen as the default choice for analyses in space and mode. Consequently, the competiveness ratio for the 'Auto – Local' alternative is consistently 1.0 across the analysis. In the case of competitiveness ratios across time, the denominator in the calculation shifts across the timescale about the time of analysis *t*.

Each trip record documented the conditions of a trip between a pair of Mobility Hubs that utilized one space-mode alternative, at a specific point in the timescale, and in a single direction of travel. This section offers an overview of the major observations and findings from analysis of the competitiveness ratios. Detailed outputs from this part of the analysis have been included in Appendix B of this thesis.

4.4.1 *Opportunities to Shift Travel in Space and Mode*

Comparison of the competitiveness ratios across space and mode reveals a number of key themes and findings. At a high level, auto alternatives generally out-performed the transit alternatives in all travel corridors within the analysis. While some corridors did have transit alternatives that were competitive to the 'Auto – Local' alternative for some parts of the day, the 'Auto-Highway (No Tolls)' and 'Auto-Highway (With Tolls)' alternatives remain more competitive for the majority of the analysis timescale. The competitiveness ratios for space and mode by time of day have been plotted for each travel flow, and are shown in Figures 13 to 24.

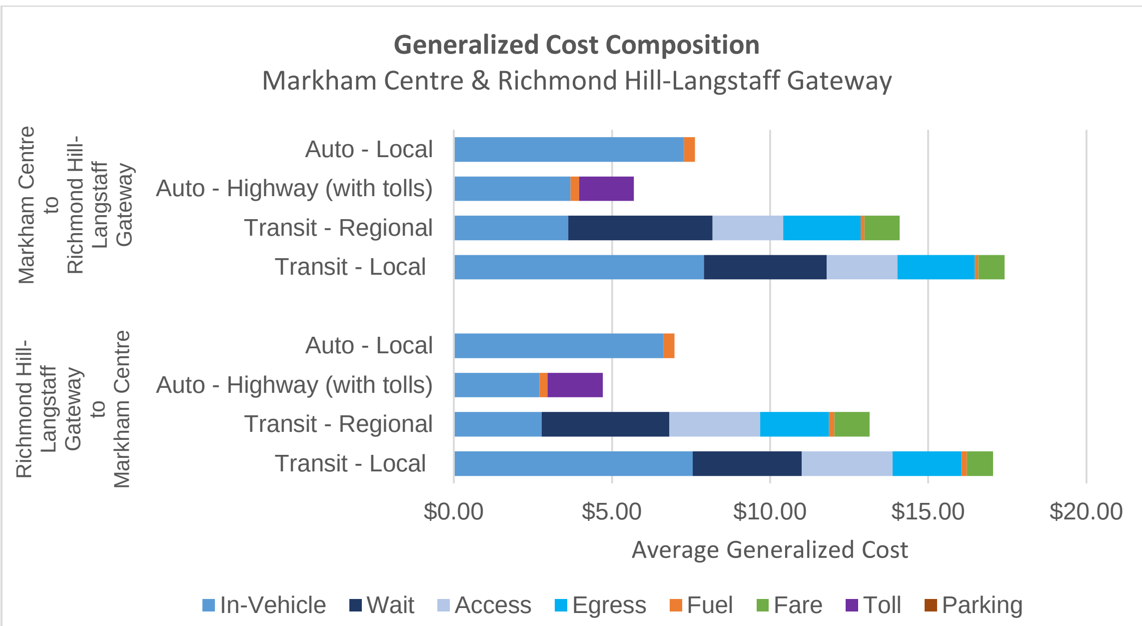
Two observations pertain specifically to the corridors that include the Union Mobility Hub as one part of the origin-destination pair. The first is that the competitiveness ratios appear to indicate a directional imbalance. Competitiveness ratio values for trips toward Union range from around 1.0 to just over 1.5, while values for trips from Union to the other Mobility Hubs range from around 1.0 to over 2.5. This aligns intuitively with what is known of the region—that the historically radial nature of the region has resulted in much better transit access into downtown Toronto than to other parts of the region. Similarly, competitiveness ratios for transit services tended to be greater in the morning and smaller in the afternoon for travel away from Union, but smaller in the morning and greater in the afternoon for travel to Union. A possible explanation for this is that the transit services in the region, specifically GO Transit regional services, tend to fluctuate over the course of the day according to commuting flows. As the area surrounding the Union Mobility Hub contains the largest concentration of employment within the region, services toward Union tend to be more frequent in the morning, which makes the burden of wait times smaller than it would be during the afternoon.

The second observation about the Union Mobility Hub is related to competitive access modes. While the 'Auto – Highway (No tolls)' and Auto – Highway (With tolls)' alternatives appeared closely competitive across all corridors where both exist, it was only in the corridors that include the Union Mobility Hub where the 'Auto – Local' alternative becomes competitive to the other two auto-based alternatives, at least during the peak periods. A possible explanation is that the corridors of travel that connect to and from Union have reached a level of peak period congestion such that increased travel times for the 'Auto – Highway (No tolls)' and 'Auto – Highway (With tolls)' alternatives have resulted in generalized costs that are similar to the 'Auto – Local' alternative. In such a case, the potential risk of applying TDM strategies such as a flat rate toll on highway travel is that travellers may shift to local roads instead, thereby creating increased local traffic and impacts on surrounding communities. As this analysis method is detached from the volume and capacity conditions within the system, the impacts of this possible condition cannot be assessed internally. To gain further understanding of what this shift in demand may mean for receiving roadways, such as local roads, other tools, such as conventional travel demand forecasting models, would be more suitable.

The Richmond Hill-Langstaff and Markham Centre corridor, as shown in Figures 19 and 20, presented an interesting case where the generalized costs were found to be significantly higher for both regional and local transit services than for the auto alternatives, despite the fact that many of the transit services in this corridor are operated either in a protected right-of-way, or on the 407 ETR tolled highway which is typically maintained in free-flow. A disaggregation of the generalized cost components for travel in this corridor, averaged across the timescale, revealed that the in-vehicle travel time components of the transit alternatives were actually quite comparable to that of the auto based alternatives. As shown in

Figure 12, the cost of in-vehicle travel time for the 'Transit – Regional' alternative were actually comparable to that of 'Auto – Highway (with tolls)' alternative, while in-vehicle travel times for the 'Transit – Local' alternative were only slightly greater in cost than the in-vehicle time of the 'Auto – Local' alternative. The largest cost components outside of in-vehicle travel time are wait time, access time, and egress time. This suggests that strategies that improve the wait times, access times, and/ or egress times would likely be needed to create any substantial change in travel behaviours in this corridor of travel.

Figure 12 –Generalized Cost Composition in Markham Centre & Richmond Hill-Langstaff



Lastly, both the Markham Centre & Mississauga City Centre and Richmond Hill-Langstaff Gateway & Mississauga City Centre corridors followed a similar pattern where the 'Transit – Regional' alternative was found to be closely competitive to the 'Auto – Local' option, while the two other auto-based alternatives outperformed it. Given the large difference in generalized cost between 'Transit – Regional' and the two auto highway alternatives, it is unlikely that TDM strategies will be sufficient in inducing adjustments to travel behaviour and thus other solutions may be needed.

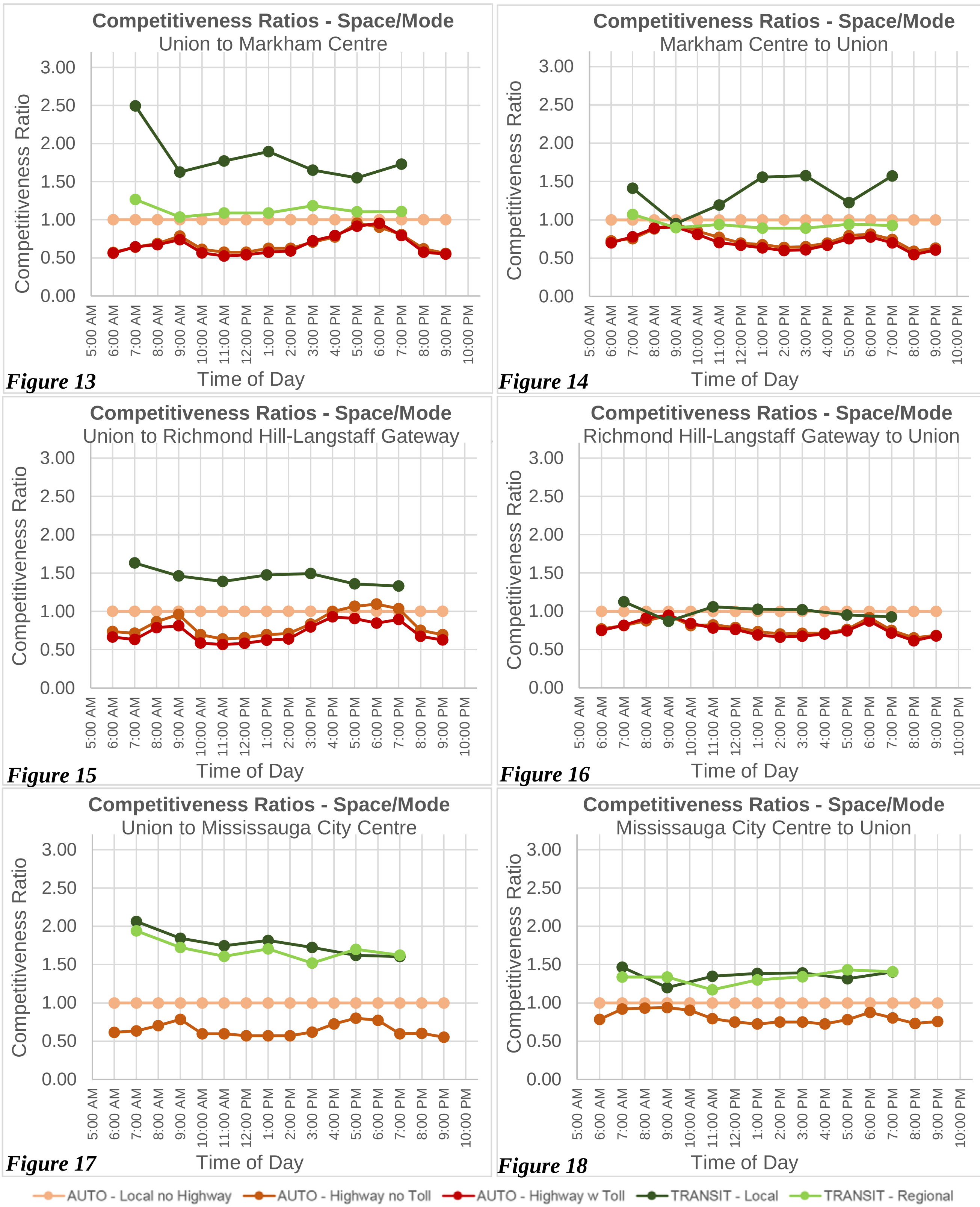


Figure 13 ***Figure 14*** ***Figure 15*** ***Figure 16*** ***Figure 17*** ***Figure 18***

Figures 13 to 18 – Competiveness Ratios – Space/Mode across Time of Day

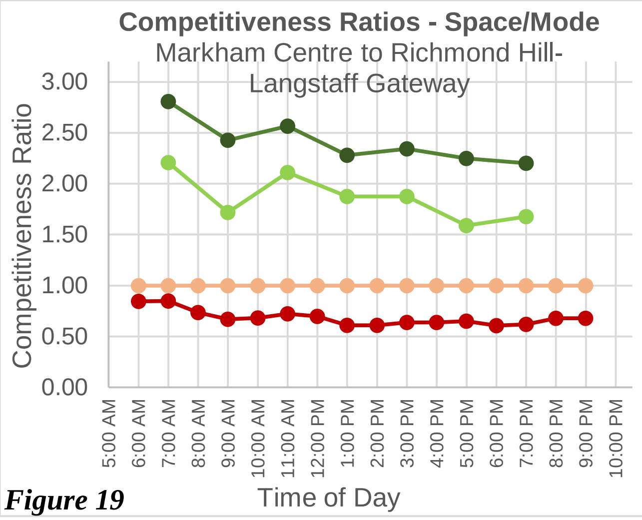


Figure 19

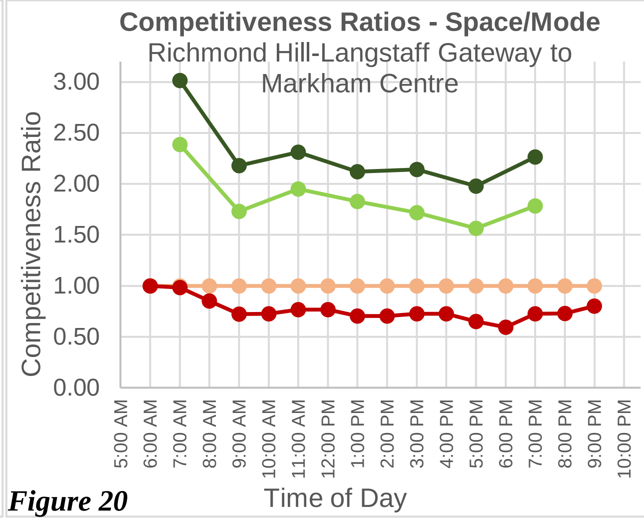


Figure 20

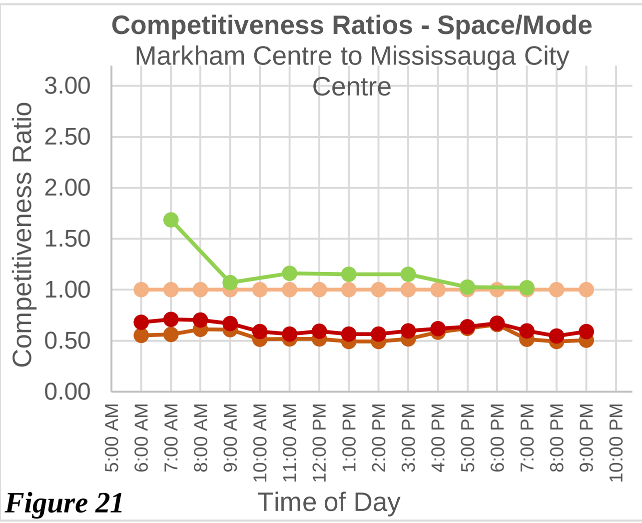


Figure 21

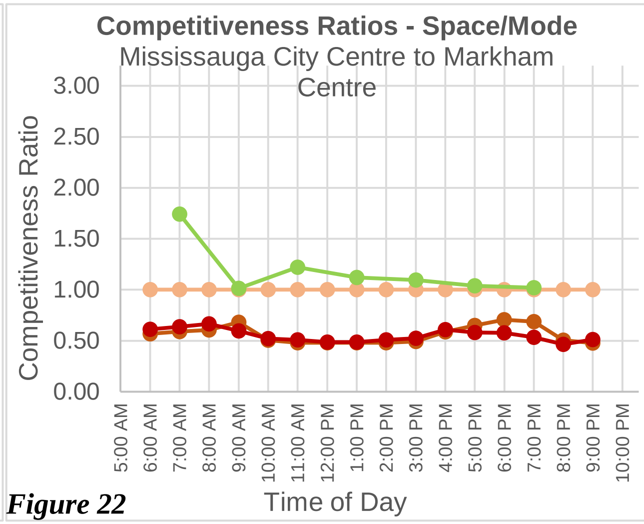


Figure 22

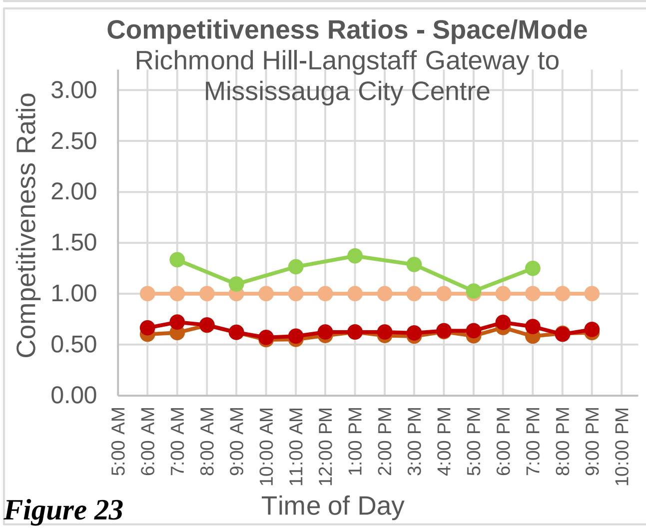


Figure 23

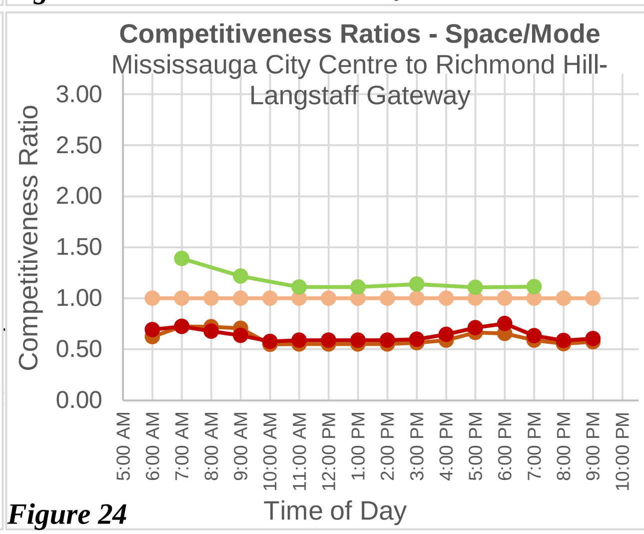


Figure 24

AUTO - Local no Highway AUTO - Highway no Toll AUTO - Highway w Toll TRANSIT - Local TRANSIT - Regional

Figures 19 to 24 – Competiveness Ratios – Space/Mode across Time of Day

4.4.2 *Opportunities to Shift Travel in Time*

Competitiveness ratios that compare generalized costs across time were calculated for one hour prior and one hour after the intended time of arrival of each trip (*t - 1* and *t + 1*). Penalties for *EARLY* and *LATE* arrival were not included in the generalized cost calculations for *t* – 1 and *t* + 1 in order to allow for better understanding of the actual conditions of travel during those times. These penalties are applied to the analysis in the testing of potential TDM strategies, presented in section 4.5.

Figures 25 and 26 plot the competitiveness ratios for opportunities to shift in time for the Union & Markham Centre corridor as an example of the reporting outputs generated in this analysis. Results for the remaining corridors have been included in Appendix B of this thesis. A review of the outputs reveal that although the fluctuations in competitiveness ratios varied from corridor to corridor, there exists an underlying pattern that is consistent across the analysis. Most of the corridors showed a similar relationship across the three auto-based alternatives, where fluctuations across time of day are more prominent across the highway alternatives than in the local alternative, with the exception of the Markham Centre & Richmond Hill-Langstaff Gateway corridor where the Auto-Highway with tolls alternative were more consistent throughout the day. For all corridors, competitiveness ratios at 9 AM and 6 PM for both *t* – 1 and *t* + 1 were less than 1.0, signifying that these are peak periods during which travel in the immediate hours before and after have a lower disutility, likely as a result of shorter travel times. In the period immediately following the 9 AM peak, most corridors showed more competitive travel for *t* + 1, the hour after, rather than *t* – 1, the hour before. However, this relationship became reversed just before the 6 PM peak, with *t* – 1 becoming more competitive than *t* +1. The pattern points generally to opportunities for more competitive travel away from the two major peaks of the day, either during the midday or before the morning and after the afternoon peak. As such, strategies that contribute to decreasing the burden of the EARLY and LATE penalties for the periods before and after the peaks could have potential impact on shifting travel demand in time.

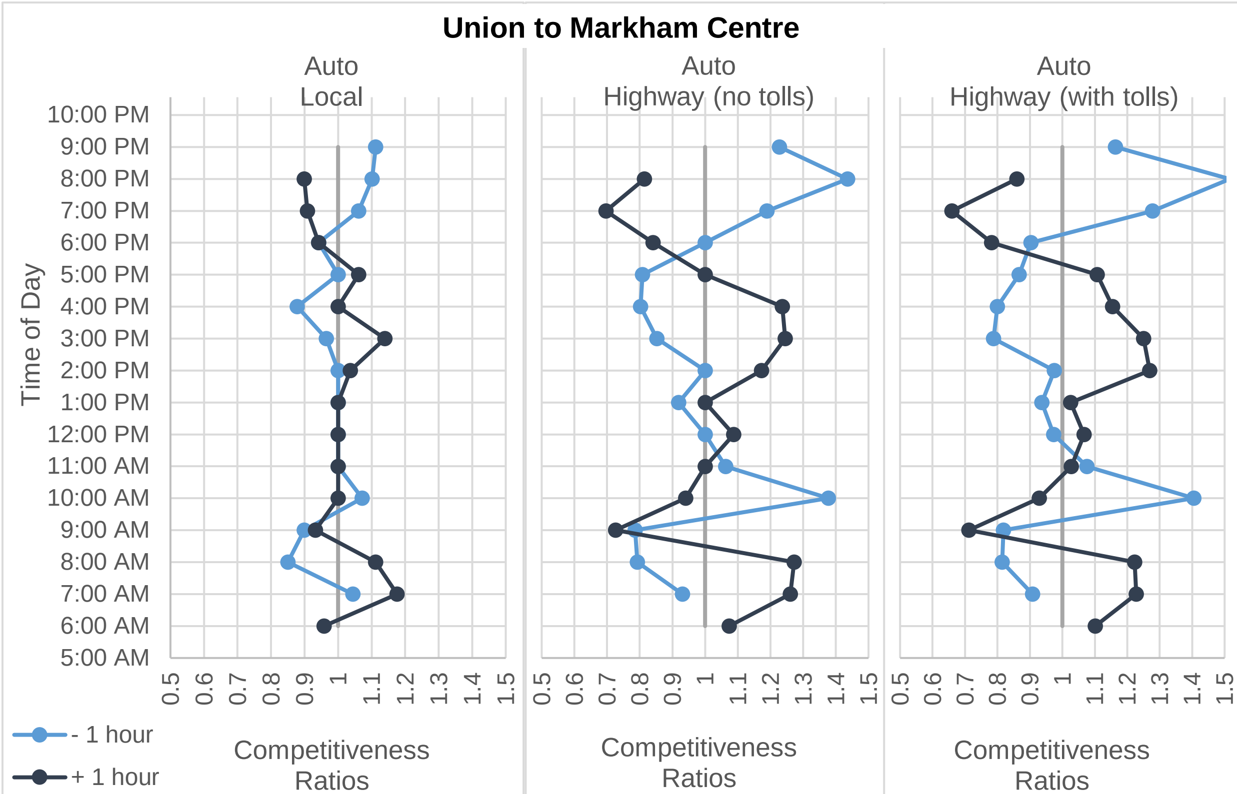


Figure 26 - Competitiveness Ratios - Time - Union to Markham Centre

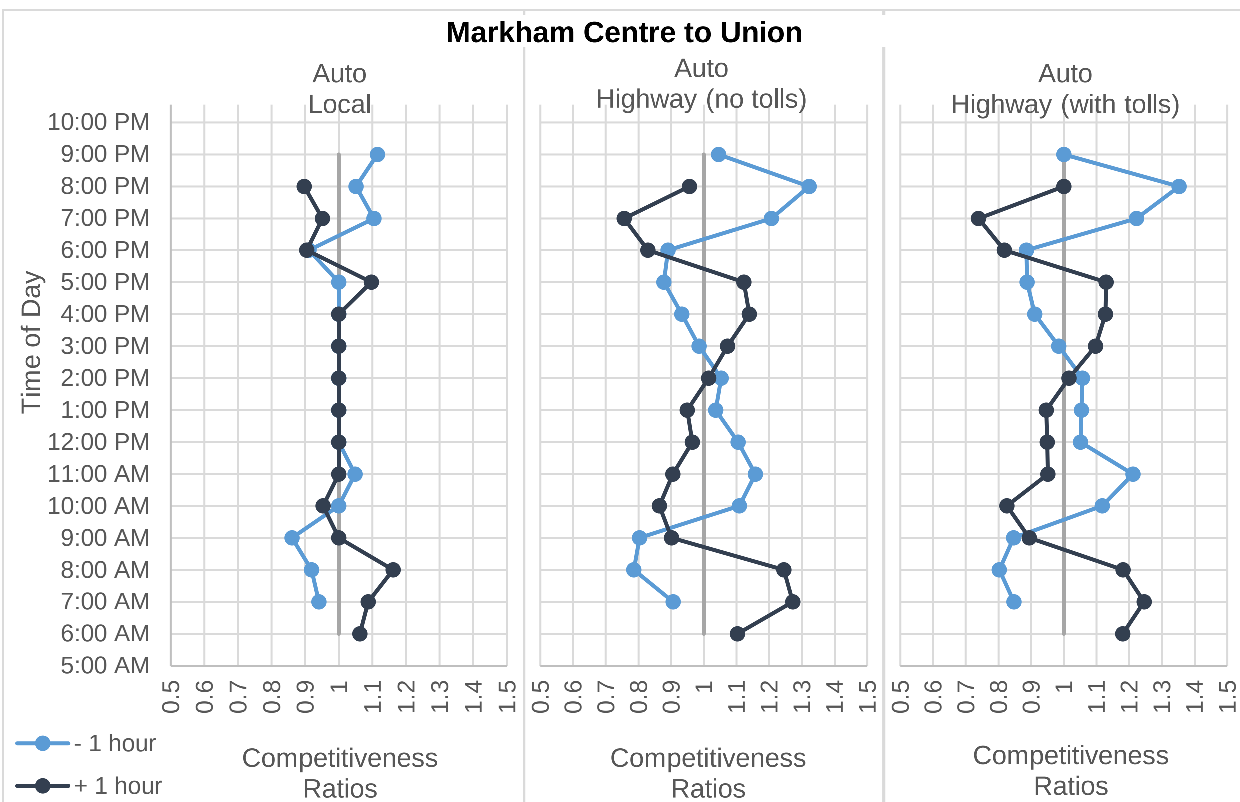


Figure 25 - Competitiveness Ratios - Time - Markham Centre to Union

4.5 MODULE 2 – EVALUATION OF POTENTIAL STRATEGIES

The second part of the TDM evaluation model was used to test potential ability of TDM strategies to shift travel behaviour across space, time, and mode. Observations drawn from the competitiveness ratios were used to inform the selection of a number of TDM strategies that could be applied to the analysis corridors, which are described further in section 4.5.2.

Using an input of generalized costs calculated from earlier steps in the process, the model was first used to estimate the starting choice share of alternatives within an established choice set which forms the frame of analysis. Then, employing the pivot-point formulation described in section 3.7, new choice shares were calculated to account for the impacts of each of the selected TDM strategies, applied at varying degrees of intensity. The following sections provide further detail on how this part of the model has been applied along with an overview of the analysis outputs generated.

4.5.1 *Establishing Choice Sets*

The scanning window, as described in section 3.6, confines the available alternatives across space, time, and mode within the choice set. Space and mode alternatives can be considered interchangeably depending on the mode of the default choice. If an auto-based alternative is selected as the default alternative, then other available auto alternatives are considered as options in space while available alternatives by other modes such as transit would be considered options in mode. As such, the space and mode alternatives are considered together.

While any available alternative, including transit-based alternatives, can also be chosen as a default, selection is limited by the quality of the data available. As the data collected for transit in this analysis have a time granularity of two hours, shifts in time within a transit alternative would be problematic to evaluate. An early or late arrival of two hours is likely to incur a large penalty, such that the resulting generalized cost would make any shift in time appear uncompetitive. As such, this specific application of the model limits the default alternative to only auto-based alternatives. Since the 'Auto – Local' alternative is consistently available across all analysis corridors and has data available on an hourly basis, it was selected as the default alternative. As such, the 'Auto – Highway (No Tolls)' and 'Auto – Highway (With Tolls)' alternatives have been identified as alternatives in space while the 'Transit – Local' and 'Transit – Regional' have been considered as the alternatives across mode.

The third dimension of the scanning window is time, which is anchored by the default time of t. The default time is the time at which the hypothetical traveller desires to arrive at their destination. As discussed in the methods section of this thesis, the time dimension of the choice set is bounded by $t \pm q$, q being the time variance from time t in hours. In this application of the model, q is equal to 1 hour, indicating that the scanning window constrains the choice set to arrival times one hour before, and one hour after the intended time of arrival.

To provide a comprehensive picture conditions across time of day, the scanning window is shifted across values of t from the period between 7 AM to 7 PM at two hour intervals (*t = {7am, 9am, 11am, 1pm, 3pm, 5pm, 7pm})*. This timescale follows the data collection schedule described in section 4.3.2.

4.5.2 *Selection of Test TDM Strategies*

Building on the observations made of the competitiveness ratios across space, mode, and time, several test strategies have been selected for further exploration. The strategies are as follows:

1. **A flat rate toll charge on all currently non-tolled highways in the region.**
   Applied to the 'Auto – Highway (no tolls)' alternative for all corridors, and to 'Auto – Highway (with tolls)' alternative in corridors where there is partial use of a non-tolled highway (which includes all corridors with the exception of the Markham Centre & Richmond Hill-Langstaff Gateway corridor). The toll charge is applied in varying intensities at increments of one dollar from $1 to $5.

Table 9 – GC adjustments for the addition of a flat rate toll charge

Alternative	**Δ GC**
Auto – Highway (no tolls)	$\{\beta_{toll}*1,\ \beta_{toll}*2,\ \beta_{toll}*3,\ \beta_{toll}*4,\ \beta_{toll}*5\}$
Auto – Highway (with tolls) *(excluding Markham & Richmond Hill-Langstaff Gateway corridor)*	$\{\beta_{toll}*1,\ \beta_{toll}*2,\ \beta_{toll}*3,\ \beta_{toll}*4,\ \beta_{toll}*5\}$
Auto – Local **Auto – Highway (with tolls)** *(Markham & Richmond Hill-Langstaff Gateway corridor)* **Transit – Local** **Transit – Regional**	*no change*

2. **A reduction in wait times for regional transit.**

   Applied to the 'Transit – Regional' alternative for all corridors. Wait time reduction is applied at varying intensities in increments of two minutes from two to ten minutes.

Table 10 – GC adjustments for reductions in regional transit wait times

Alternative	**Δ GC**
Transit – Regional	$\{\beta_{wait}*\text{-}2*VOT,\ \beta_{wait}*\text{-}4*VOT,\ \beta_{wait}*\text{-}6*VOT,\ \beta_{wait}*\text{-}8*VOT,\ \beta_{wait}*\text{-}10*VOT\}$
Auto – Local **Auto – Highway (no tolls)** **Auto – Highway (with tolls)** **Transit - Local**	*no change*

3. **Flexible work hours / late start program.**

   Applied to the base choice ('Auto – Local') at time t + 1. A reduction to the *LATE* arrival penalty is applied varying intensities of 1/5 increments, from 1/5 * LATE upwards to 5/5 * LATE (or complete removal of the *LATE* arrival penalty).

Table 11 – GC adjustments for flexible work hours / late start program

Alternative	**Δ GC**
Auto – Local (at time t +1)	{- 1/5 * LATE, - 2/5 * LATE, - 3/5 * LATE, - 4/5 * LATE, - LATE}
Auto – Highway (no tolls) **Auto – Highway (with tolls)** **Transit – Local** **Transit – Regional**	*no change*

4. **A flat rate toll charge on all currently non-tolled highways in the region combined with a decrease in regional transit wait times.**

   A flat rate toll charge applied to the 'Auto – Highway (no tolls)' and 'Auto – Highway (with tolls)' alternatives as per strategy 1, with the addition of a complementary 5 minute decrease in wait time for 'Transit – Regional'.

Table 12 – GC adjustments for the addition of a flat toll charge and reduced wait times

Alternative	**Δ GC**
Auto – Highway (no tolls)	{β_{toll} *1, β_{toll} *2, β_{toll} *3, β_{toll} *4, β_{toll} *5}
Auto – Highway (with tolls) *(excluding Markham & Richmond Hill-Langstaff Gateway corridor)*	{β_{toll} *1, β_{toll} *2, β_{toll} *3, β_{toll} *4, β_{toll} *5}
Transit – Regional	{β_{wait}*-2*VOT}
Auto – Local **Auto – Highway (with tolls)** *(Markham & Richmond Hill-Langstaff Gateway corridor)* **Transit – Local**	*no change*

4.5.3 *Estimate of Starting Choice Share*

To establish the base conditions, starting choice shares were estimated using the calculated generalized cost values. Table 13 shows averages of the calculated starting choice share outputs. Although this overview masks some time of day variations (such as higher levels of transit use expected during peak periods), it reveals several points that may be useful in directing future improvements to the model.

The first point of note is that the shares across the three auto alternatives are significantly higher than the shares of the transit alternatives. While the observed mode shares reported through the Transportation Tomorrow Survey do indicate high levels of auto-dependency, the average values estimated using the model greatly surpass the empirical values for the category of 'Driver' over a 24-hour period (Data Management Group, 2011) . This is particularly unusual as the timescale used in this analysis is focused around the peak periods and peak shoulders of the day when transit service should be most attractive, rather than over the course of a 24-hour period where an average of transit shares may be diluted by the lack of transit service available in off-peak periods of the day. As a point of comparison, shares for ‘Driver’ were reported at around 60% to 80% both to and from the municipalities, excluding Downtown Toronto (Data Management Group, 2011). However, when the categories of ‘Driver’ and ‘Passenger’ are combined, the reported share values for these same municipalities range from 80% to just under 90%, which is closer to what has been estimated from the generalized cost values using the model presented.

Table 13 - Estimate of Starting Choice Shares

Origin	Destination	AUTO - Local	AUTO - Highway (no toll)	AUTO - Highway (with tolls)	TRANSIT - Local	TRANSIT - Regional	1 hour prior t-q	1 hour after t+q	TOTAL	AUTO	TRANSIT
Union	Markham Centre	2.09%	38.22%	59.38%	0.00%	0.31%	0.00%	0.00%	100.00%	99.69%	0.31%
Markham Centre	Union	0.58%	28.64%	63.29%	1.49%	6.00%	0.00%	0.00%	100.00%	92.50%	7.49%
Union	Richmond Hill-Langstaff Gateway	5.64%	19.56%	74.78%	0.02%	0.00%	0.00%	0.00%	100.00%	99.98%	0.02%
Richmond Hill-Langstaff Gateway	Union	0.72%	30.95%	57.46%	10.87%	0.00%	0.00%	0.00%	100.00%	89.13%	10.87%
Union	Mississauga City Centre	1.60%	98.40%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	0.00%
Mississauga City Centre	Union	6.41%	93.53%	0.00%	0.03%	0.02%	0.01%	0.00%	100.00%	99.95%	0.05%
Markham Centre	Richmond Hill-Langstaff Gateway	10.66%	0.00%	89.31%	0.00%	0.03%	0.00%	0.00%	100.00%	99.97%	0.03%
Richmond Hill-Langstaff Gateway	Markham Centre	15.09%	0.00%	84.88%	0.00%	0.02%	0.00%	0.00%	100.00%	99.97%	0.02%
Markham Centre	Mississauga City Centre	0.00%	82.32%	17.68%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	0.00%
Mississauga City Centre	Markham Centre	0.00%	41.34%	58.66%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	0.00%
Richmond Hill-Langstaff Gateway	Mississauga City Centre	0.03%	68.89%	31.08%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	0.00%
Mississauga City Centre	Richmond Hill-Langstaff Gateway	0.08%	60.44%	39.48%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%	0.00%

100% of Choice Share

0% of Choice Share

Across the corridors, the shares for ‘Auto – Highway (with tolls)’ also appear to be quite high when compared to the other two auto based alternatives. Since this analysis emphasizes intercity trips, which tend to be longer in distance, lower shares of ‘Auto – Local’ travel is not unreasonable. However, the corridors of Union & Markham Centre, Union & Richmond Hill-Langstaff Gateway show exceptionally high estimates for travel by ‘Auto – Highway (with tolls)’ even as compared to ‘Auto – Highway (no tolls)’.

In the case of the Markham Centre & Richmond Hill-Langstaff corridor, since there is no viable ‘Auto – Highway (no tolls)’ option available, the ‘Auto – Highway (with tolls)’ also takes a significant portion of the auto share. While this corridor also shows noticeably higher ‘Auto – Local’ shares than in other corridors due to the lack of ‘Auto – Highway (no tolls)’ option, the ‘Auto – Highway (with tolls)’ alternative takes a significantly larger portion of the share of estimated travel. This would seem to go against conventional understanding as toll roads are typically priced in a way that maintains a state of free-flow to ensure reliability for its users. If the ‘Auto – Highway (with tolls)’ option is truly as attractive as the estimates suggest, one might expect much higher levels of usage, which would likely in turn result in higher toll charges to maintain service levels high and travel volumes at a manageable level. These points suggest potential issues of calibration. Since this analysis uses default coefficient measures from literature to weigh the relative cost of different variables in the generalized cost calculations, there may be some discrepancy with how costs are perceived by travellers within the geographical context of the analysis. More specifically, since the coefficient value for tolls was not reported in the documentation of the COMMUTER model on which this model has been based, the coefficient value for parking was adopted as a proxy. Further discussion on the impact of changes to the coefficient value is discussed in section 5. For the purpose of this analyses, a coefficient of 0.322, a default value adopted from literature, is maintained for toll charges. Section A.10 under Appendix A includes further explanation of how this coefficient was chosen.

In Table 13, several values have been blocked out either because they do not exist as viable alternatives for the specified corridor (as in the case of the 'Auto – Highway (No Tolls)' alternative for the Markham Centre & Richmond Hill Langstaff Gateway corridor), or as a result of data collection error stemming from limitations in the capabilities of Google Maps. Issues with data collection mainly impacted the transit alternatives. In the case of the Union & Richmond Hill-Langstaff Gateway corridor, the issue stemmed from the inability of the Google Maps web mapping interface to recognize nearby 'Transit – Regional' services located approximately 500m away from the anchor point. As a result, the choice share estimates for this corridor are likely to be inaccurate as the values were not calculated with consideration for the availability of those services. This limitation of the Google Maps data points to potential issues that may limit its usability on a larger scale where data cannot be reasonably validated for consistency with real life conditions. Further discussion of this data limitation, and a potential solution to address this challenge are discussed in section 5.3. It should also be noted that the choice share estimates are indicators for the relative attractiveness of the alternatives according to their generalized cost, and not actual estimates of actual decision making as other variables, such as the volume and capacity associated with the alternatives, and household resources would also have to be considered.

4.5.4 *Sensitivity Testing of TDM Strategies*

To gain a better understanding of how the model responds to inputs of TDM strategies, sensitivity tests were conducted using the TDM Strategies described in section 4.5.2. Employing the pivot-point formulation described in section 3.7, new sets of choice shares were estimated for each choice set, reflecting the varying intensities at which each TDM strategy is applied. This section presents a summary of the impacts observed, focusing on a select number of sample corridors that best exemplify the impacts of the TDM strategies and the performance and capabilities of the model. A more comprehensive set of model outputs that show the changes across all the corridors has been included as part of Appendix C

TDM Strategy 1 - Flat Rate Toll Charge on Non-Tolled Highways

The first TDM strategy tested is a flat rate toll charge on all highway facilities that are currently not tolled. This charge was applied to all instances of the ‘Auto – Highway (no tolls)’ alternative, as well as most instances of ‘Auto – Highway (with tolls)’ as segments of travel are completed on non-tolled highway facilities. Out of the corridors analysed, the Markham Centre & Richmond Hill-Langstaff Gateway corridor is the only one excluded from analysis as the alternatives available do not include travel on any non-tolled highways.

As expected, the model estimates that a toll charge on the non-tolled highway facilities would result in increases to the shares of ‘Auto – Local’ and the available transit options. Most of the corridors show noticeable responses to the toll charge, with the exception of the Markham Centre & Mississauga City Centre and Richmond Hill-Langstaff Gateway & Mississauga City Centre corridors, which show only nominal change. In the case of these two corridors, the shift in behaviour occurs mainly between the ‘Auto – Highway (with tolls)’ and ‘Auto – Highway (no tolls)’ alternatives as the generalized costs even out. This aligns with the earlier stated observations of the competitiveness ratios, which identified little opportunity for behavioural shift in these two corridors as the two highway alternatives greatly outperform the transit alternatives available.

In the Markham Centre & Union Corridor, shown in Figures 27 and 28, shares for ‘Auto – Local’ increase proportionally to the increased toll charge for travel in the direction of Markham Centre. In the opposing direction, ‘Transit – Regional’ and ‘Transit – Local’ alternatives that lead toward Union see a major increase in usage during the AM peak, with nominal increases in shares through the rest of the day. Interestingly it appears that shift potential exists only in the AM and PM peaks, which in some ways confirms the findings from initial screening of the competitiveness ratios, which showed the competitiveness ratios for transit coming closest to 1.0 or less only around the peaks.

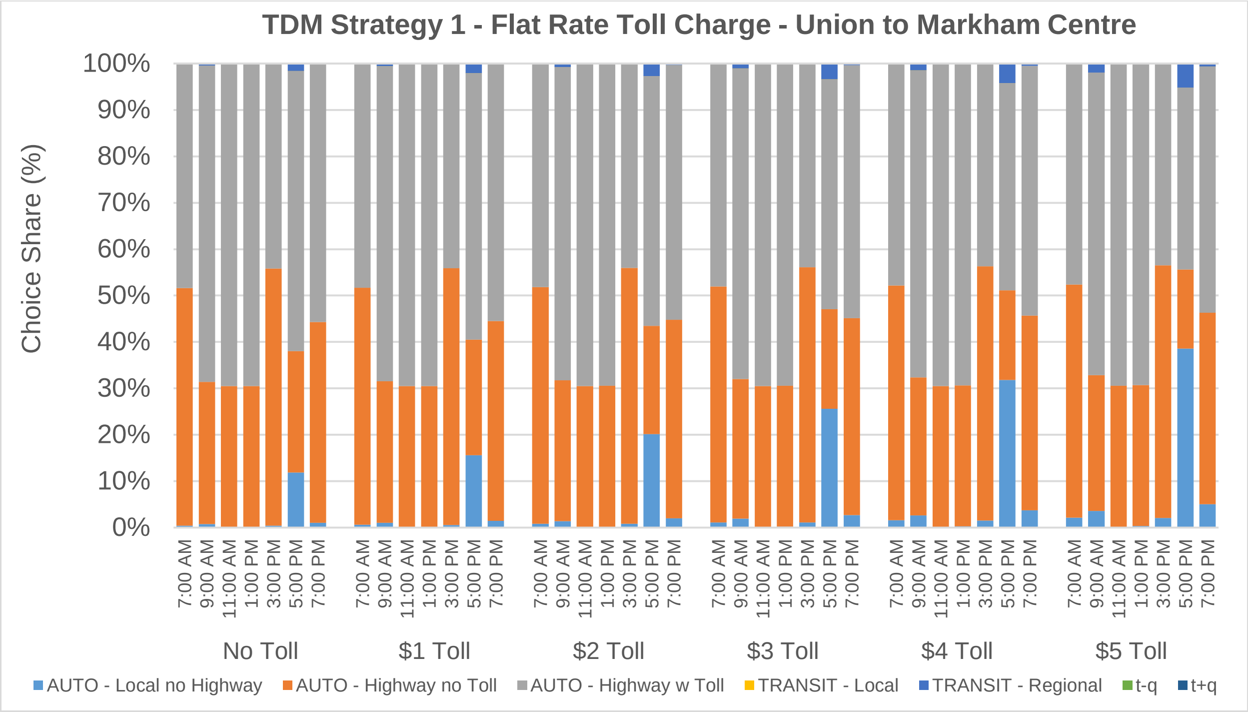


Figure 27 – Application of Flat Rate Toll Charge – Union to Markham Centre

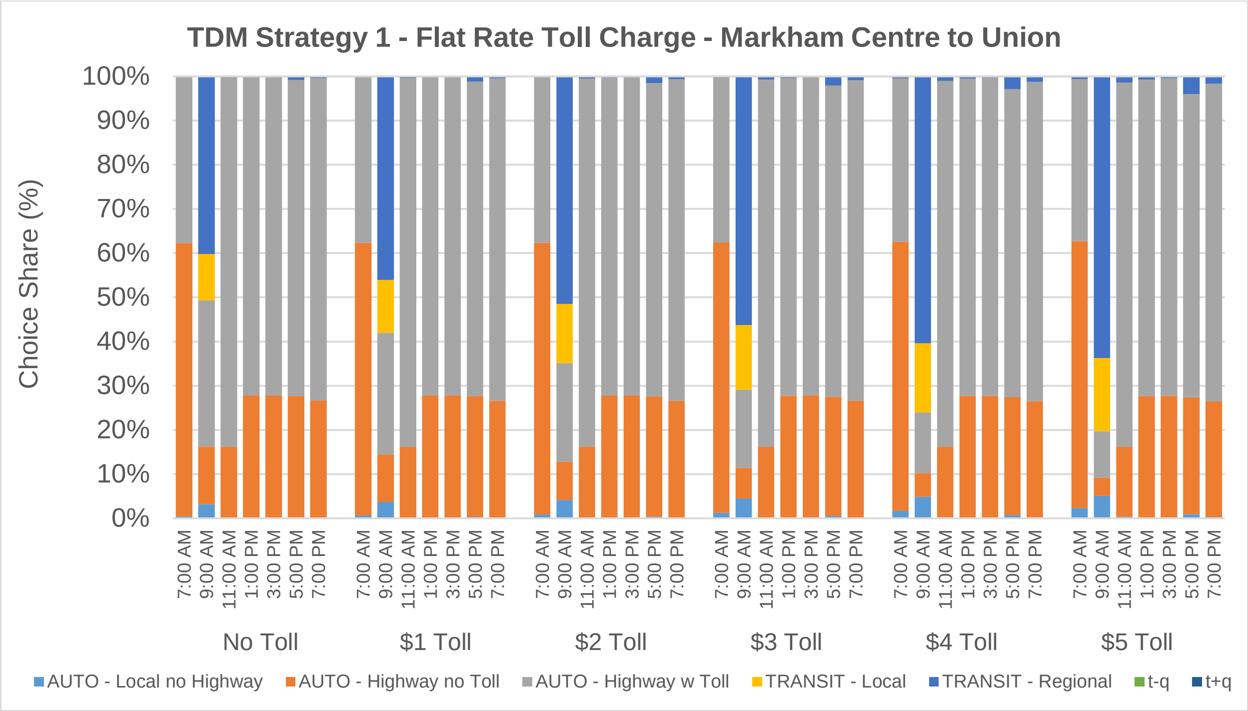


Figure 28 – Application of Flat Rate Toll Charge – Markham Centre to Union

The new choice shares generated for the Union & Richmond Hill-Langstaff Gateway corridor similarly suggest increases in auto-local shares travelling away from union and increases in transit shares travelling towards union, particularly in the peak periods for transit travel. This further reinforces the notion of an underlying imbalance in services along corridors that connect to the Union Mobility Hub. However, a point worth noting is that the estimated shares for local transit travel are exceptionally high, reaching over 91% at the 9 AM arrival time when a $5 toll charge is applied. A review of the generalized costs for this corridor finds that for travel in the direction of Union, costs for auto increase to surpass that of the 'Transit – Local' alternative at 9 am, likely a result of congestion related increases to travel time. Even still, such a dramatic increase in shares of transit travel seem unlikely, particularly given the relatively small price of the toll charge, and may be telling of issues with the model structure or calibration. Figures 29 and 30 show the evolution of choice shares for the Union & Richmond Hill-Langstaff Gateway corridor in response to the toll charge.

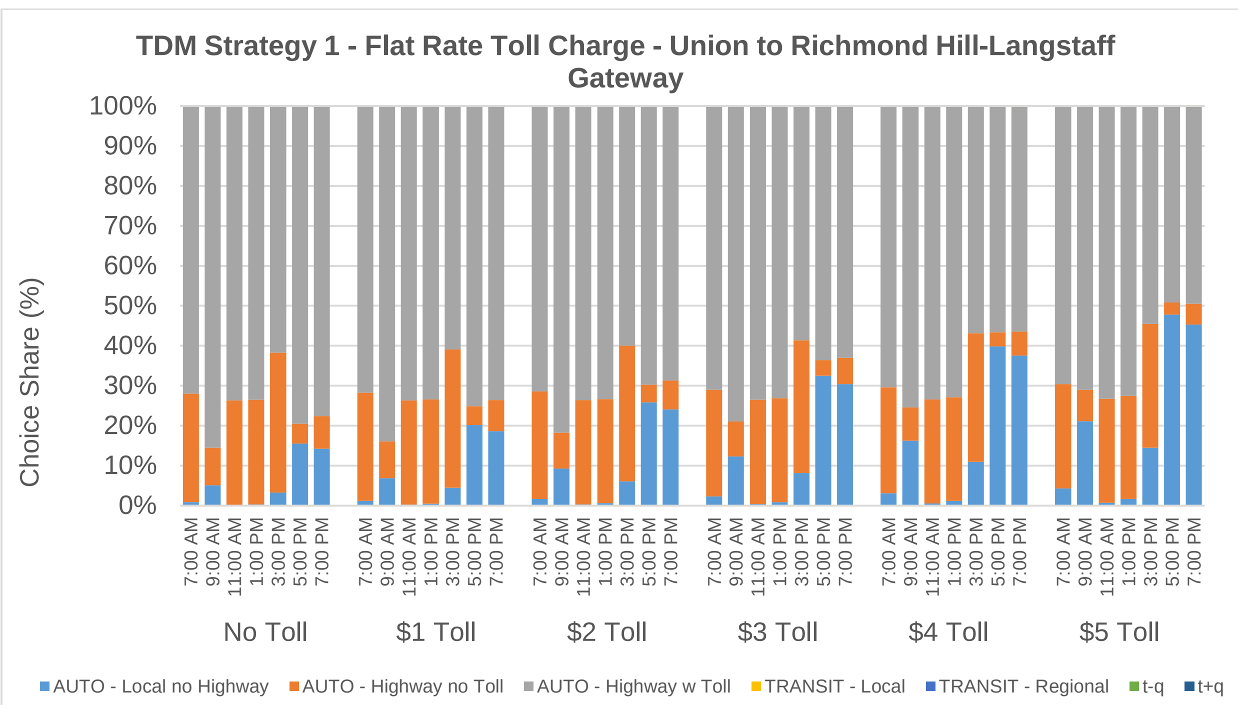


Figure 29 – Application of Flat Rate Toll Charge – Union to Richmond Hill-Langstaff Gateway

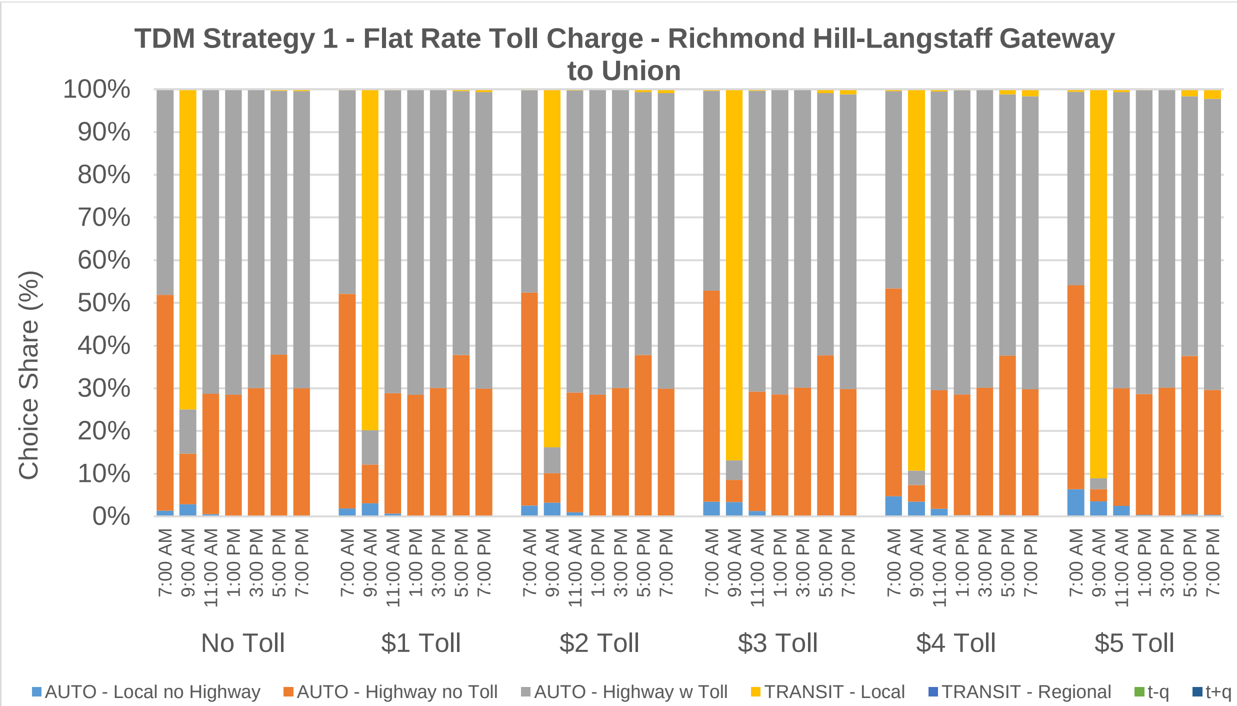


Figure 30 - Application of Flat Rate Toll Charge – Richmond Hill-Langstaff Gateway to Union

TDM Strategy 2 – Decrease in Regional Transit Wait Times

The second TDM strategy tested is aimed at creating mode shift by improving the attractiveness of transit travel. Since wait times make up a substantial part of the travel cost for transit travel, decreases in transit wait times are expected to have an impact on travel behaviour. For most corridors of analysis, the model estimates at least some increase in transit choice shares. The impact is most prominent in the Union & Markham Centre corridor, and particularly for travel in direction of Union during the AM peak periods. Given a 10 minute decrease in transit wait times, the model estimates choice shares for the ‘Transit – Regional’ to reach upwards to 98.8% of all trips at 9 am. Similar to the dramatic impacts observed in the application of TDM strategy 1, such a substantial shift seems quite unreasonable, and potentially points to the need for reconfiguration of the model or calibration beyond the use of coefficient values from literature. Nevertheless, the elastic nature of this response relative to the other corridors of analysis suggest that there is indeed opportunity for alternatives such as transit to be made more competitive in this corridor, though likely not to the same degree as estimated. A more subtle impact is the decrease in shares of local transit travel in the direction of Union as the wait times for 'Transit – Regional' decrease. Although the attractiveness of transit increases on a whole, this would suggest that improvements to one transit alternative has the potential to not only draw choice share away from autos, but also away from other transit modes. Figures 31 and 32 provide an overview of the model estimated changes in choice share for this corridor, given incremental decreases to transit wait time.

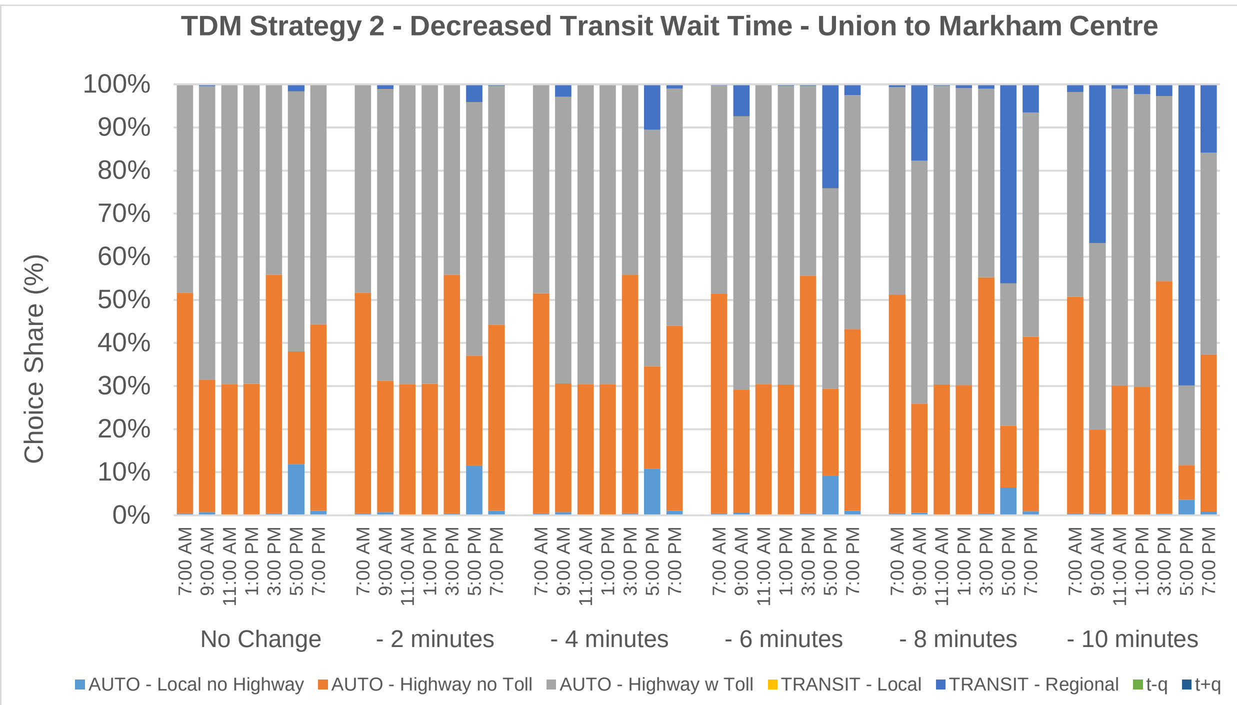


Figure 31 – Application of Decreased Transit Wait Time – Union to Markham Centre

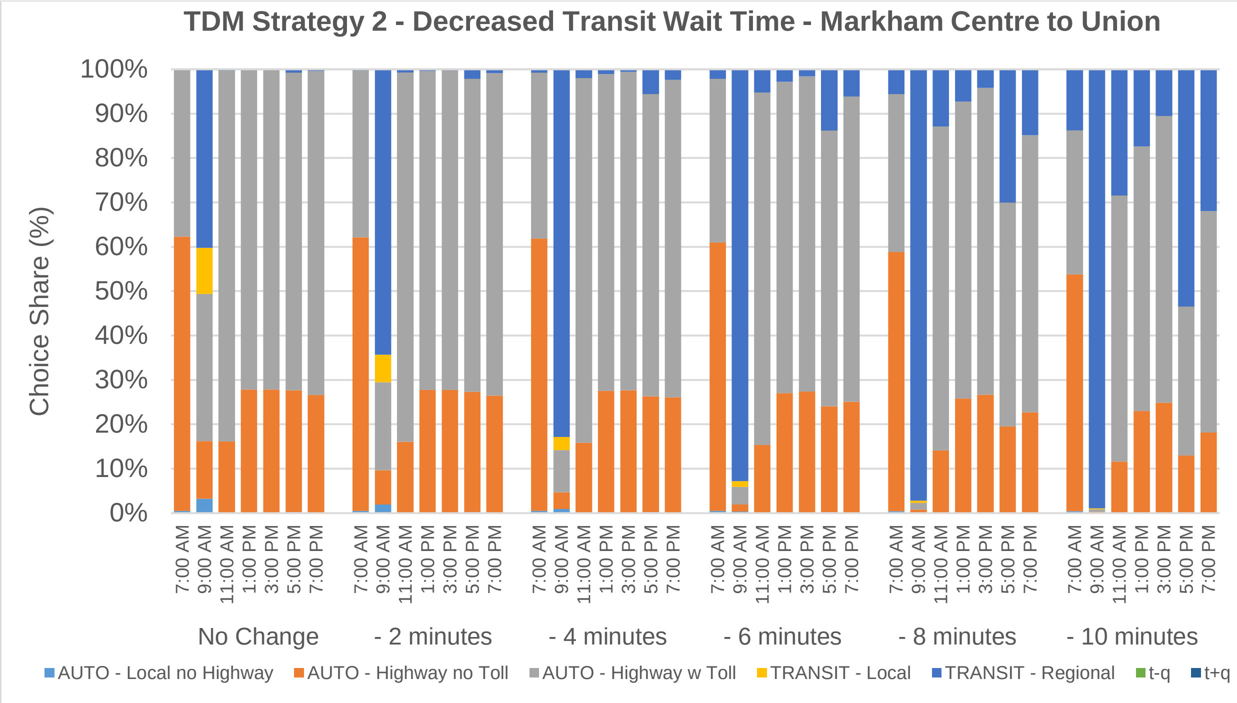


Figure 32 – Application of Decreased Transit Wait Time –Markham Centre to Union

Contrary to the Union & Markham Centre Corridor, the Union & Mississauga City Centre and Markham Centre & Richmond Hill-Langstaff Gateway corridors were quite insensitive to the wait time savings, showing only some indication of increased transit shares as the wait time decrease approaches between 6 to 10 minutes. Lastly, changes to the choice shares for the Richmond Hill-Langstaff Gateway & Mississauga City Centre and Markham Centre & Mississauga City Centre corridors were almost undetectable. This lack of sensitivity aligns with what the earlier competitiveness ratio analysis showed, that transit remains largely uncompetitive within this corridor.

TDM Strategy 3 – Flexible Work Hours

The third TDM strategy has been chosen with the intent of exploring potential opportunities to shift travel demand in time. As the addition of the EARLY and LATE penalties make it such that travel during t -1 and t +1 are completely out of consideration, this strategy explores the opportunity for shift should the burden of a LATE penalty be decreased or removed altogether. Although flexible work hours would likely remove the burden of being late to one's work, a late start to work may also result in some personal disutility of other forms, stemming from issues such as having to work later, or being unable to make subsequent appointments and responsibilities in time (such as picking up children from the daycare). As such, the penalty has been deducted incrementally to reflect the limitations of flexible work hour programs in reducing the *LATE* burden.

The results of the pivot-point analysis showed that partial decreases in the *LATE* penalty had little benefit to increasing the likelihood of travel during times t +1. It is only when the *LATE* penalty is deducted in its entirety that changes in the choice share of $t + 1$ are observed. As expected, the greatest opportunities exist after 9 am, and after 6 pm. In some cases, such as in the Union & Mississauga City Centre corridor shown in Figures 33 and 34increases in the shares of t +1 manifest later in the day, which could potentially signal a wider afternoon peak than morning peak.

Overall, the impacts of this strategy were limited across the board which is to be expected since the 'Auto – Local' alternative showed competitiveness ratios for both $t+q$ and t-q that hovered around 1.0 during the midday, which indicates the generalized cost remain fairly consistent over time. Application of this strategy with a more volatile alternative as the base might produce very different results.

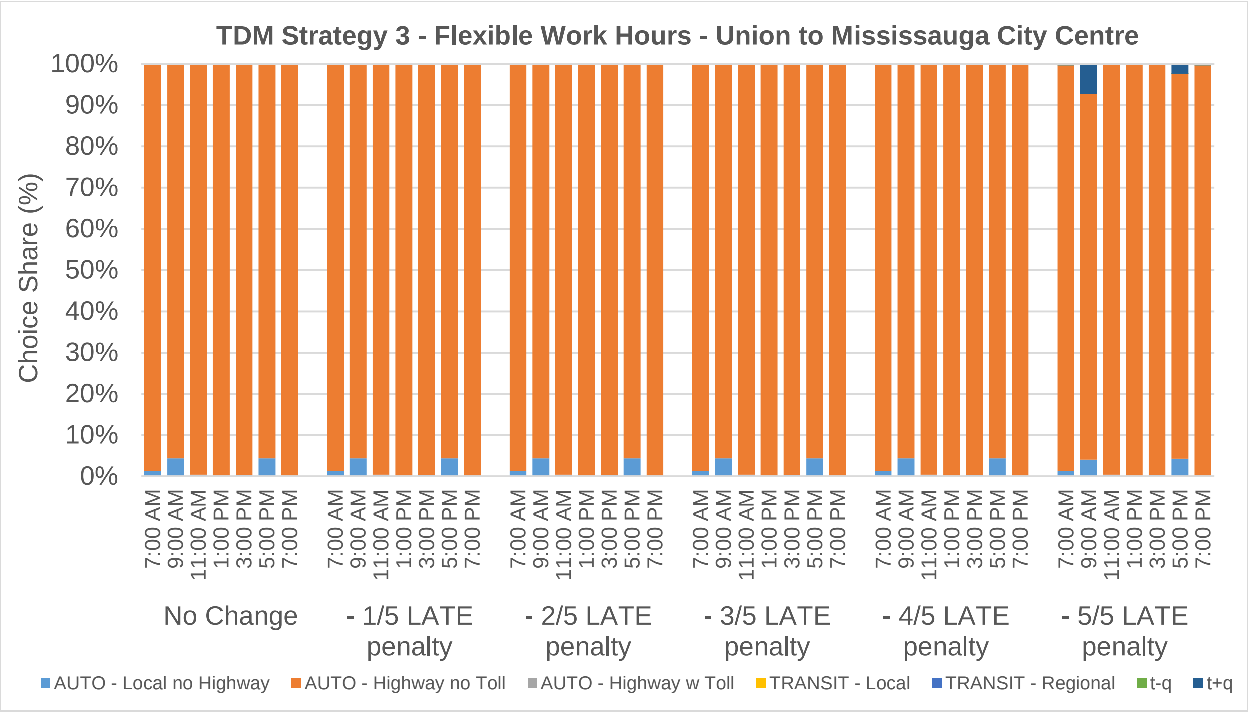


Figure 33 – Application of Flexible Work Hours – Union to Mississauga City Centre

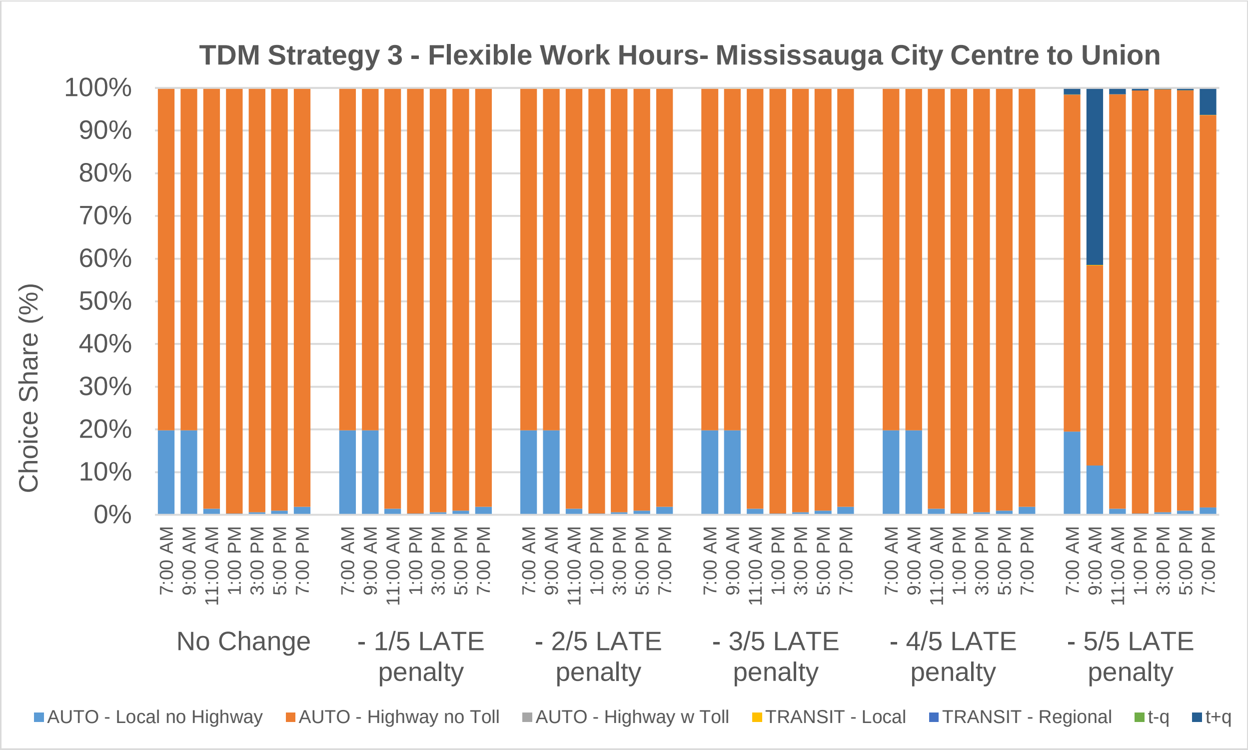


Figure 34 – Application of Flexible Work Hours – Mississauga City Centre to Union

TDM Strategy 4 - Flat Rate Toll Charge on Non-Tolled Highways and a reduction in wait times for regional transit.

Lastly Strategy 4 is used to test the model's ability to handle interactions. Combining Strategies 1 and 2, a flat rate toll charge of varying intensities is applied in increments of $1 from $1 to $5, along with a static 5 minute reduction in regional transit wait time.

As compared to Strategy 1, the inclusion of an additional 5 minute wait time decrease has contributed to an intensification of the impacts. As shown in Figure 35 and 36, the increase in shares for 'Transit – Regional' are significantly larger than they are in the analysis of Strategy 1 for the Union & Markham Centre corridor. The addition of the 5 minute reduction in regional transit wait times has also resulted in some shift in shares from 'Transit – Local' to 'Transit – Regional', something that was not observed in the analysis of TDM Strategy 1, but did manifest in the analysis results of TDM Strategy 2.

Similar to the analysis of Strategies 1 through 4, the choice shares for the Markham & Mississauga City Centre and Richmond Hill-Langstaff Gateway & Mississauga City Centre corridors show negligible response to the strategy, even with the combined effects of both tolling and wait time reductions. This suggests that more fundamental changes may need to be made in this corridor if transit options are to be competitive to auto.

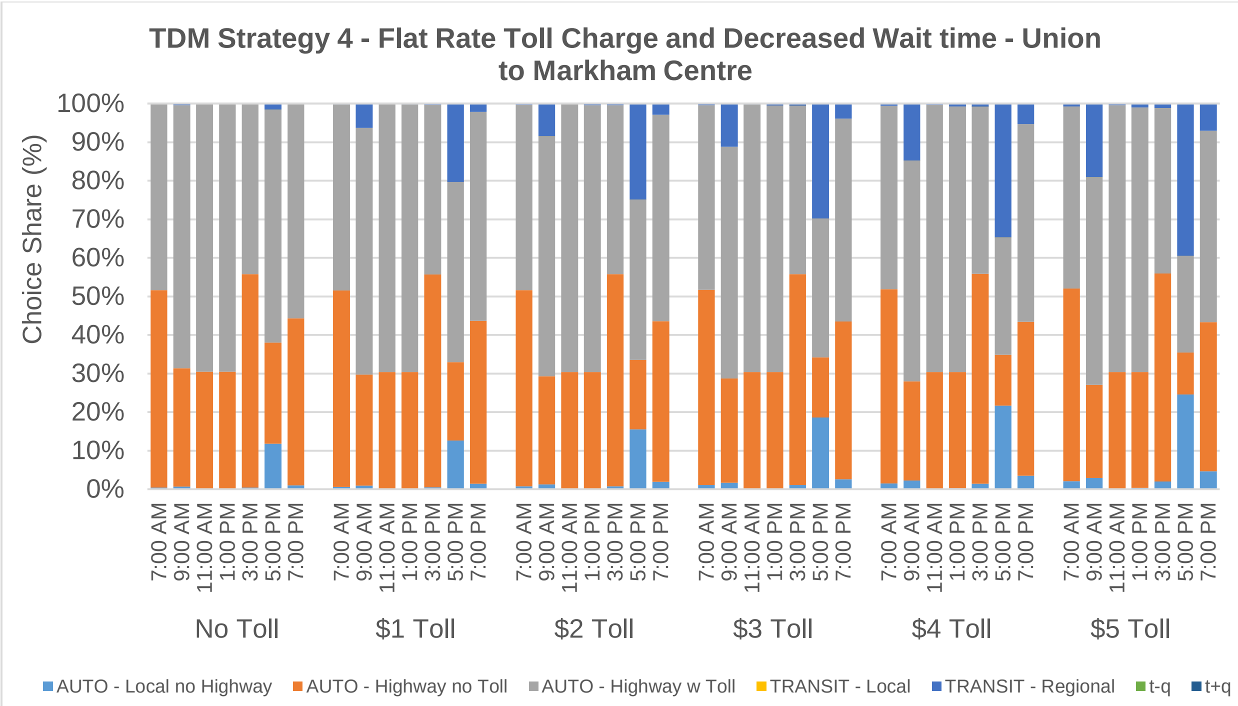


Figure 35 – Application of Flat Rate Toll Charge and Decreased Wait Time – Union to Markham Centre

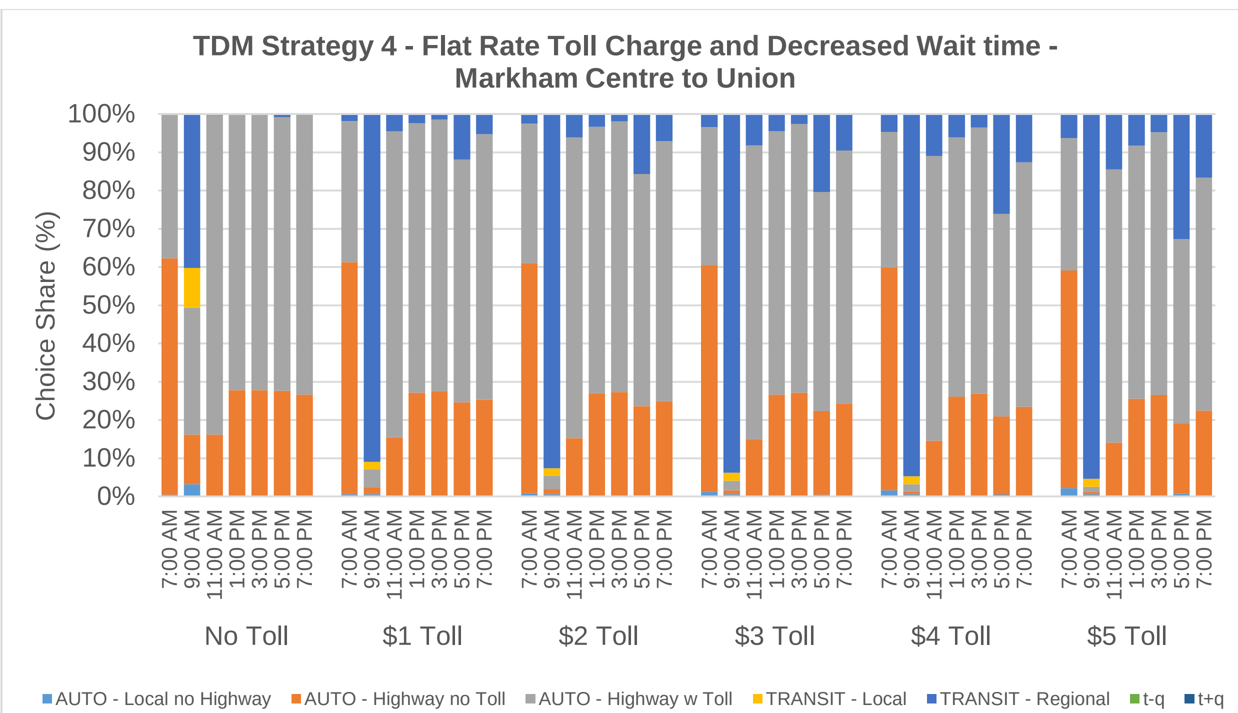


Figure 36 – Application of Flat Rate Toll Charge and Decreased Wait Time – Markham Centre to Union

4.6 CHAPTER SUMMARY

Employing the methods described in chapter 3 of this thesis, an analysis was conducted on a set of travel corridors in the GTHA to explore potential opportunities for TDM strategies to be applied. Four designated Mobility Hubs within the region were selected as the origin-destination points for the analysis, making for a total of six analysis corridors, and consequently twelve directional flows.

In this section, each of the corridors were put through the analysis framework starting from collection of travel data through Google Maps, to identification of opportunities for TDM, and through to the evaluation and sensitivity testing of potential TDM strategies.

Generalized costs were calculated for alternatives across space, mode, and time according to the travel data sourced mainly from Google Maps. While the data effectively met the travel data requirements of the model framework, a number of challenges associated with the data were also highlighted. Further discussion of these issues and potential methods for mitigating the barriers identified are discussed in the following chapter.

The first part of analysis compared alternatives across each of the corridors on the basis of competitiveness ratios calculated off the generalized costs. The results of the analysis generally aligned with what is intuitively known of the travel corridors. In particular, the analysis of alternatives across space and mode revealed a strong directional imbalance in corridors that involved the Union Mobility Hub as either an origin or destination, which makes sense given that it is the major transportation hub in the region and is located at the core of the region's largest employment centre. The analysis revealed that travel by transit tend to be more competitive in the direction of the Union Mobility Hub during the AM peak period, and inversely more competitive in the opposite direction during the PM peak period, which is in line with the dominant commuting patterns to and from this centre.

The second part of the analysis assessed the effectiveness of selected TDM strategies in shifting. A total of four strategies were chosen, including the addition of tolls on currently non-tolled highways, decreases in transit wait times, programs that allow for flexible work times, and a combination of tolls and transit wait time improvements. Building off of estimated starting choice shares, the model estimated changes to the shares in response to varying intensities of TDM strategy application. In all, the results of the analysis aligned directionally with what one would expect from an assessment of opportunities for TDM in the selected corridors and within the context of the GTHA. However, the magnitude of change estimated by the model for some of the strategies may be cause for caution. For one, nominal increases in toll charges resulted in much stronger shifts from auto-based modes to transit than what might be expected in real life application. As an example, in the Markham to Union travel flow, the addition of a $5 toll on currently non-tolled highways resulted in a sharp increase in the choice share of regional transit from approximately 40% to more than 90%. Although an increase in tolls may in fact drive some increase in the share of transit usage, such a large change is unusual. This points to possible issues within the model, such as the calibration of coefficients, or potentially missing variables that need to be internalized. Further discussion of the challenges experienced in the application of the model framework is discussed in chapter 5.

5.0 DISCUSSION AND CONCLUSIONS

This thesis set out to develop a set of techniques that would be useful in identifying and evaluating corridors of travel for opportunities to apply TDM strategies. Complementary to this, the applicability of crowdsourced travel data from web mapping applications such as Google Maps in transport analyses is also explored. A review of literature was conducted to explore the roots of TDM and past models that have been used to assess the performance of TDM strategies prior to implementation. Research was also conducted on current and emerging practices in travel data collection, namely location enabled data using technologies such as GPS. Based on the findings of the literature review, a model framework was developed and applied to a set of test corridors within the GTHA. Chapter 6 described the procedure taken to apply the model, along with major findings and observations that came out of the application process. Out of the model application process, several challenges and issues relating to the data collection and model framework were identified. This section elaborates further on some of these challenges and describes potential paths to addressing these concerns.

5.1 SUMMARY OF RESEARCH

A simple framework for analyzing potential opportunities to apply TDM strategies has been presented in this thesis to target an audience of transport practitioners who may not have the in-house capabilities or resources to execute more complex travel demand models. The model framework builds on techniques employed by past TDM evaluation models used in practice, such as the EPA COMMUTER model, with adjustments made to analyze a suite of alternatives across space, time, and mode, and to better utilize travel time data sourced from Google Maps. The two stage model framework first identifies opportunities for TDM application through a comparison of generalized costs by way of competitiveness ratios. The second module then estimates the baseline traveller choices from the generalized costs using a multinomial logit model, and subsequently employs a pivot-point logit model to estimate changes in traveller choice as a result of TDM strategies that impact the generalized cost.

The model framework has been applied to a set of corridors in the Greater Toronto and Hamilton Area that connect growth nodes called Mobility Hubs. While collection of Google Maps travel time data for the study corridors was simple and straightforward for auto travel, collection of transit travel data proved to be quite challenging. Validation of route recommendations through human judgement was required to correct for irregularities in the suggested routings, and the addition of external data sources such as transit schedule data was required to supplement the data outputs. Application of the model also revealed potential issues relating to the model structure and calibration. While the model was able to respond directionally in appropriate ways, identifying and estimating potential opportunities for TDM where generalized costs were truly competitive, the magnitude of change in response to some TDM strategies appears to be overestimated. The following section elaborates on some of the limitations that have emerged.

5.2 LIMITATIONS

Application of the model has revealed a number of limitations associated with the use of Google Maps travel time data, as well as with the model formulation. First off, the use of Google Maps travel time data as opposed to more conventional forms of travel data comes with certain challenges. While the Google Maps data provide the benefit of granularity both in the timescales at which the data is available and in the level of disaggregation of trip-leg level data, there is little research available to confirm the accuracy of the data to actual travel conditions. Secondly, as Google Maps is a proprietary product, the underlying methods used for calculating predictive travel times are not known.

Data collection through Google Maps also proved to be quite challenging, particularly in terms of transit travel data. Although unconfirmed, the search algorithm used to select route recommendations seemingly placed heavy penalties on walk access to transit access locations. In the case of travel between the Richmond Hill-Langstaff Mobility Hub and the Union Mobility Hub, Google Maps failed to recognize transit services located approximately 500m away from the anchor point of Richmond Hill-Langstaff Gateway, and instead suggested a circuitous route that would have taken a significantly longer amount of time and resulted in a much greater user disutility. As fare information is not included with the available transit data, Google Maps also had trouble differentiating between local transit services, and regional transit services which were significantly more expensive. Many route recommendations non-discriminately mixed regional and local transit services in ways that would be unlikely for a traveller who is presented with actual fare costs to contend with. It is not known whether Google Maps takes fares into consideration for jurisdictions that do supply the fare data through GTFS. Such challenges put into question the accuracy and suitability of transit route recommendations generated by the web mapping application.

In terms of analysis capability, the model appears to respond accordingly to selected TDM strategies by adjusting the shares of alternatives where opportunities are available (i.e. where generalized costs of competing alternatives were competitive). However, where the model estimates share adjustments, the magnitude of change is in some cases larger than what one might expect. As an example, choice shares for the 'Transit – Regional' alternative in the Markham Centre to Union flow of travel changed from 49.2% to 98.8% in response to a decrease of 10 minutes in regional transit wait times. Similarly, in the same corridor, a flat rate toll charge in all increments resulted in a significantly larger increase in transit shares than shares of 'Auto – Local'. Although possible, it is quite unlikely that a nominal change in wait times would result in a near complete shift of travellers away from auto and on to transit, or that a change in auto costs would shift more travel to transit than to another auto alternative. One explanation for this inaccuracy is a possible violation of the Independence of Irrelevant Alternatives (IIA) property required in discrete choice theory. Though treated as distinct alternatives in this model, the alternatives presented have inherent similarities that should in reality lead to more likely shifts in choice shares between some alternatives rather than others. For an individual traveller who is accustomed to auto travel, a shift between travelling by auto on a highway to travelling by auto on local roads is likely less onerous than a shift towards transit travel. More empirical data would be needed to conduct the statistical testing required to identify a more appropriate alternatives setup that is consistent with the IIA property, but a possible remedy may be to reconfigure the model alternatives from the standard multinomial logit form, to a nested logit model (Cheng & Long, 2007; Minal, 2014).

Another possible explanation for inaccuracy within the model results could be issues with model calibration. In the absence of local trip survey data, it was not possible to calibrate the model to local conditions. Although coefficient values or weights for cost variables within the literature were found to be within a similar range, there were still some jurisdictional variations. The model as it stands does not fully illustrate conditions within the study area of the GTHA, and for any future application, should be calibrated to the conditions of the local area. There were also specific model coefficients for which values were not available, such as for toll charges. In this application of the model, the coefficient reported for parking charges in the COMMUTER model documentation was used as a proxy for the coefficient value for toll charges, as both can be considered out-of-pocket costs. However, it is quite possible that travellers may value parking and tolls quite differently. Using the shares for the Markham Centre & Richmond Hill corridor as an example, changes to the coefficient of the toll cost variable upwards to 1.0 (which would suggest the tolls are valued at the true cost) result in a significant shift in the distribution of shares between the alternatives, and more specifically between 'Auto – Local' and 'Auto – Highway (with tolls)'. Figures 37 and 38 show the change in shares as a result of adjustments to the coefficient for toll charges (β_{toll}).

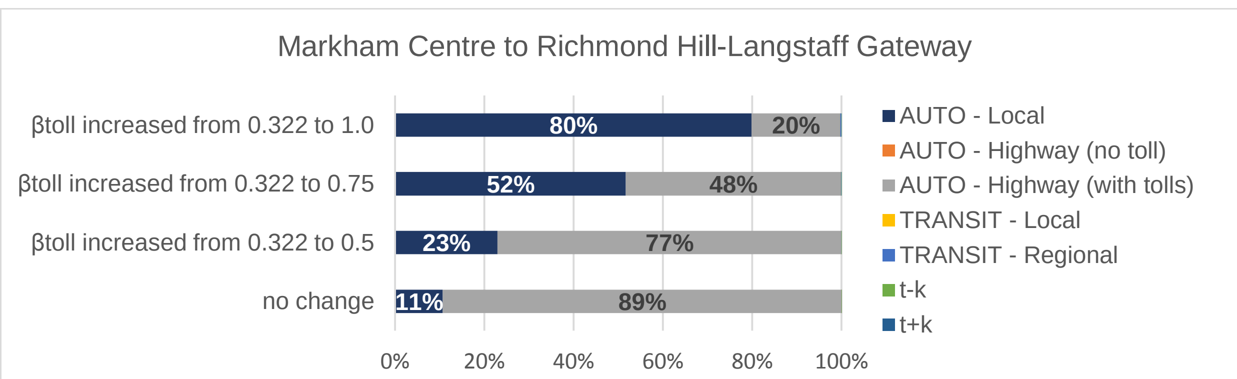


Figure 37 – Sensitivity of Choice Share Shifts as a function of Toll Charge Coefficient (1)

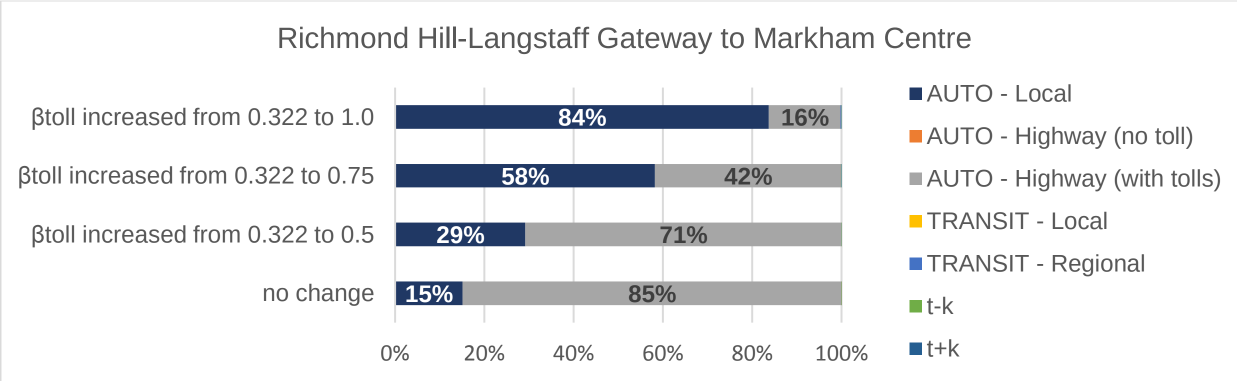


Figure 38 – Sensitivity of Choice Share Shifts as a function of Toll Charge Coefficient (2)

The accuracy of the model may also be improved through calibration to corridor level choice shares. Although empirical data is rarely disaggregated to the level of the space and mode classifications presented in this thesis, it may be possible to calibrate starting the choice shares generated by the model to empirical mode shares at an aggregate level.

5.3 FUTURE RESEARCH

This thesis has revealed a number of opportunities for future research pertaining to both the use of Google Maps travel time data, and the analysis methods employed in the model. A review of the literature around crowdsourced location data finds that there are few studies that evaluate the accuracy of widely accessible data sources such as Google Maps. Opportunity exists to build on the work of Wang & Xu (2011) to expand the body of knowledge around crowdsourced location data. Improved understanding of how Google Maps travel time projections compare to empirical data would be of particular value.

Further exploration of data collection techniques used in the collection of Google Maps data would also be beneficial. In this research, the use of individual point-based data to represent origin and destination areas proved to be challenging, particularly in the collection of transit data from the Google Maps web map interface. Figure 39 illustrates a possible method that could be explored in future work. Instead of selecting specific point-based origin and destination locations to anchor each corridor, origin-destination zones could be represented by two sets of randomized points which form the anchors for multiple paths of travel between the origin-destination zones. Travel time between the origin and destination zones could then be generalized as an average of those paths of travel instead of being represented by travel along a single route.

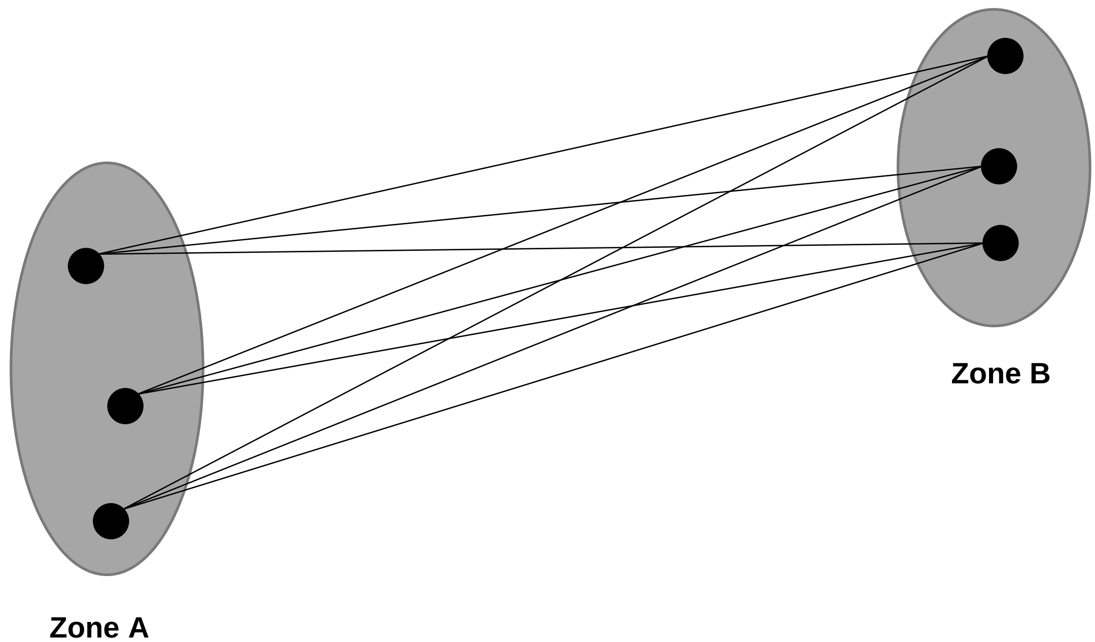


Figure 39 - Conceptual diagram for multi-point data sampling technique

In terms of the analysis methods used, future research should be focused on either improving on the capabilities of the model framework presented, or on exploring other behavioural models that may be more suitable. Calibration of the existing model framework would be a logical first step to improving the accuracy of model estimations. Appendix D provides an overview of procedures that could be used to calibrate the model. Future research should be conducted to explore other discrete choice models to replace the parts of the analysis framework that currently rely on the use the multinomial logit model formulation. For example, a nested logit formulation may help to improve the accuracy of model estimations by making the model consistent with the IIA property. Future work on this and similar models would also benefit from improved local traveller behaviour research. Much of the research used to support the selection of the default model coefficients come from the United States.

5.4 CONCLUSIONS

The model presented in this thesis provides a framework for TDM evaluation, and is most suitable for high level, preliminary evaluations that are used to triage corridors of travel for opportunities to apply TDM strategies. However, questions of accuracy remain, thus it should only be used to direct further explorations into potential TDM strategies rather than to inform actual evaluations of TDM strategy performance. It is recommended that future models depart from the multinomial logit formulation used in order to better cope with issues related to the IIA property. Calibration of the model to empirical data would also contribute to improving the accuracy of the model results. In parallel to the model framework development, this thesis also explores a potential application of travel time data collected through Google Maps. Experience gained through manual collection of the travel time data found it to be readily usable for auto based alternatives, but less so for transit travel. A significant amount of external input is still needed in estimating travel times and costs for transit travel, whereas auto data collection could likely be automated fairly easily for collection of much larger datasets. Further research beyond the work of Wang & Xu (2011) is needed to validate the accuracy of crowdsourced data sources such as Google Maps, but in principle, the data shows promise for applications in other aspects of transportation evaluation beyond the model presented.

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APPENDIX A – Generalized Cost Functions

Generalized cost calculations typically include a linear sum of variables representing travel disutility, each calculated using different formulae that can vary across transport modes. In a generalized cost calculation, the cost of travel time associated with a given trip is typically captured in a number of separate time components. As perception of time can vary under different contexts and conditions, this disaggregation allows for weight adjustments to be made on the independent time components so that the resultant travel time costs more closely represent the disutility experienced by travellers (Iseki, Taylor, & Miller, 2006; Koppelman & Bhat, 2006; Nour et al., 2010). This appendix presents further detail on the methods used to calculate or derive each of the generalized cost variables considered in this research, as well as the coefficient values that are used to adjust the weighting of the different cost variables. Recapping the information provided in Table 2 under Chapter 3 of this thesis, the following is a list of the variables included in the generalized cost calculations:

- Access Travel Time
- Wait Time
- In-Vehicle Travel Time
- Egress Travel Time
- Parking Charge
- Fuel Cost
- Fare Charge
- Toll Charge

The coefficient values for these generalized cost variables are provided in section A.10. All coefficients are weighed against the coefficient value for In-vehicle travel time, which has been assigned a coefficient value of 1.0.

A.1 VALUE OF TIME (VOT)

To convert non-monetary time variables to be comparable in monetary terms, a Value of Time (VOT) measure is applied as a conversion factor. In travel demand modelling, the personal VOT experienced by each traveller is typically quantified as some function of the wages in the area of analysis. A common convention among researchers is to use the hourly wage rate as the perceived VOT of work-based trips (Minal, 2014). In the case of non-work based trips, some researcher suggest values closer to 25% of the hourly wage (Lesley, 2009). For the purpose of this research, the direct hourly wage[3] has been used as the VOT, calculated from median income of the census division in which each origin point is located.

Table 14 - Value of Time (VOT) by Origin Mobility Hub Location

Origin Mobility Hub	**Census Subdivision**	**Median Income for Population over 15 ($)**	**Value of Time (VOT) ($/ hour)**	**Value of Time (VOT) ($/ min)**
Markham Centre	Markham	$ 27,157	$13.93	$0.232
Mississauga City Centre	Mississauga	$ 29,837	$15.30	$0.255
Richmond Hill-Langstaff Gateway	Richmond Hill	$ 30,532	$15.66	$0.261
Union	Toronto	$ 27,371	$14.04	$0.234
Source: 2011 National Household Survey				

A.2 ACCESS TRAVEL TIME (t_{access})

Access travel time refers to the time that travellers spend getting from their place of origin to the primary mode of their trip. It is a common component in the generalized cost for transit calculation as most conventional transit is accessible only at transit stops and stations, and travellers are often required to travel some distance to access the service. While auto travel could also perceivably include an element of access travel time (i.e. time taken to travel from a place of origin to the location of the parked vehicle), this is typically negligible as parking is often readily available at both origin and destination locations across the region. This ease of access to parking is one contributing factor to the attractiveness of the personal automobile among travellers in the GTHA.

As the origin-destination locations used in this research are all designated Mobility Hubs, which are intended to be major points of transit access, the data collected inherently does not include significant

[3] Hourly wage was calculated by dividing the median income by 52 weeks, assumed to contain 37.5 working hours per week. A second VOT value presented in $/ minutes has been provided for ease of calculation

amounts of access time. However, as the majority of Mobility Hubs are still under development, few commuters live in the direct vicinity of these transit access areas. Metrolinx has published a set of Mobility Hub profiles which include information on the 85th percentile station access distances for Mobility Hubs that include a GO Transit Rail station (17 out of the 51 Mobility Hubs). For the purpose of this analysis, origin-destination Mobility Hubs that have a GO Transit Rail station adopt the 85th percentile station access distance reported in the Mobility Hub profile. All other mobility hubs use an access distance of 5km, which is the modal distance across the 17 Mobility Hubs with reported station access information. Table 15 presents assumed station access distance and modes used for each origin Mobility Hub, established according to information published in the Metrolinx Mobility Hub profiles.

Table 15 - Access assumptions by origin Mobility Hub

Origin Mobility Hub	**85th percentile Station Access Distance**	**Most Common Access Mode**	**Travel Speed (km/h)**
Markham Centre	5.5 km	Auto	50
Mississauga City Centre [4]	5 km	Auto	50
Richmond Hill-Langstaff Gateway	3.8 km	Auto	50
Union [5]	0.4 km	Walk	5

A.3 WAIT TIME (t_{wait})

The cost of wait time is intended to capture the perceived disutility that a traveller experiences from having to await the arrival of a transport service. Commonly associated with conventional transit services, the wait time cost is also applicable to other transport services such as taxis and ridehailing services, as well as other shared and on-demand mobility services.

[4] As there is no published data for Mississauga City Centre, a default distance of 5km has been used.
[5] From a regional context, Union serves more as a destination rather than origin. In line with the assumption for the egress time variable, a walking distance of 400m has been used.

In the case of conventional transit, wait time is typically calculated as a function of the time headway of the service. A common approach for calculating wait time is to assume that passengers arrive at random in a normal fashion, and that the average wait time across all passengers is approximately half of the time headway (Salek & Machemehl, 1999). This method is sufficient for approximating wait times for transit services with relatively short headways, but does not rightly capture traveller behaviour for lower frequency transit trips where travellers are more likely to plan their arrivals with the intention of minimizing wait time.

A number of empirical studies point to a time headway of approximately 10-minutes as the threshold for passengers to transition from arriving at random to arriving at a planned time, though there is little agreement on an actual model that can be used for estimating wait times (Fan & Machemehl, 2002; Salek & Machemehl, 1999). In the absence of local studies to inform this relationship, this research adopts the method put forward by Casello & Hellinga, (2008), presented in Equation 10.

Equation 10 - Wait Time (t_{wait})

$$t_{wait} = \begin{cases} \dfrac{h}{2} & \text{initial } h \leq 10min.;\ transfer\ wait\ time \\ & or \\ 10 - 5e^{\left(1-\frac{h}{10}\right)} & \text{initial } h > 10min. \end{cases}$$

Where:

$h = time\ headway\ (minutes)$
$e = e\ constant$

As suggested in the equation above, the differentiation between headways of less than or equal to 10 minutes and those greater than 10 minutes in length is most relevant for the initial transit leg as it is the only part of a transit trip when travellers have the most control over the time at which they arrive at a stop or station. The wait time experienced by travellers during transfers between services is dependent on the arrival time of the transit vehicle that they are traveling in, and the departure time of the transit vehicle that they intend to transfer to. Assuming that transit service arrivals and departures are not coordinated, and in a sense, arrive at the stop or station at random, wait time can be approximated as half the departing headway.

A.4 IN-VEHICLE TRAVEL TIME (t_{IV})

In-vehicle travel time refers to the time spent during travel on the primary mode of a trip. For auto trips, this is quite straightforward as trips typically contain one continuous leg of in-vehicle travel. On transit trips, in-vehicle travel time may be segmented into a number of different legs of travel that could potentially be associated with varying degrees of service quality. For example, a traveller that takes both a regional commuter service and a local service during one trip may have two very different experiences on the two services as longer distance commuter services are often designed with more attention to passenger comfort than local short distances services. Models that are sensitive to the qualitative elements of travel may disaggregate in-vehicle travel time components to further differentiate the service quality experienced through weight adjustments. However, in the absence of data to inform the model about how the various services in the region are perceived, the cost of in-vehicle travel across all transit services in this research has been considered equally. The in-vehicle travel time for both auto and transit trips analyzed in this research has been collected directly through the Google Maps directions tool. Further discussion around the use of Google Maps as a source of travel time data can be found in section 4.3 of this thesis.

A.5 EGRESS TRAVEL TIME (t_{egress})

Egress time captures the time taken for travellers to get from the location at which they end their travel on the primary mode of a trip to the intended final destination location. Similar to access time, egress time is typical to modes such as transit, where the drop off location for the primary mode may not take the traveller to the exact destination. While auto modes could also perceivably include some measure of egress time, it is uncommon in most North American contexts, including the GTHA, as parking is often readily available. In this model, the cost of egress travel time is applied only to transit modes. Since travellers are typically limited by their access to alternative modes at the end of their travel by transit, walking is the most likely mode used. It is commonly regarded for both access and egress legs that the likelihood of travellers being willing to travel to and from a transit station decays with increased distance, though the rate at which this decay occurs differs between studies, and can be impacted by a number of factors, including the surrounding land use conditions and trip purpose. Given the lack empirical data supporting the egress behaviour of local travellers, this analysis assumes an egress distance of 400m for all trips, a rule of thumb measure that has been cited in the literature (Kim, 2015; Krygsman, Dijst, & Arentze, 2004). Given an average walking speed of approximately 5km/h, a 400m walk would take just under 5 minutes of time.

A.6 PARKING CHARGE ($C_{parking}$)

Table 16 - Average parking charge by Mobility Hub area

Mobility Hub	**Parking Entry Time**[6]	**Average Parking Charge**[7]
Markham Centre	Daytime (6:00 AM – 6:00 PM)	$0
	Evening (6:00 PM – 6:00 AM)	$0
Mississauga City Centre	Daytime (6:00 AM – 6:00 PM)	$0
	Evening (6:00 PM – 6:00 AM)	$0
Richmond Hill-Langstaff Gateway	Daytime (6:00 AM – 6:00 PM)	$0
	Evening (6:00 PM – 6:00 AM)	$0
Union	Daytime (6:00 AM – 6:00 PM)	$16.86
	Evening (6:00 PM – 6:00 AM)	$12.75

The cost of parking largely depends on the local bylaws, regulations, and market conditions of the destination location. In many parts of the GTHA, parking is provided to auto users at no cost, and in parts of the region where parking does come with a charge, the cost is often subsidized by employers as a benefit to their employees. This ease of access to parking is one contributing factor to the attractiveness of the personal automobile. As there is currently no comprehensive dataset that captures the cost of parking across

[6] A sampling of 26 parking facilities in the immediate vicinity around the Union Mobility Hub found that the majority of parking providers used 6:00 AM and 6:00 PM as the cut-off times between daytime and evening parking rates.
[7] Average parking charge calculated across both monthly and daily charges. Monthly costs were assumed to be spread over 22 working days per month. Daily charges have been capped at max rate charged for each time interval.

the region, this research adopts average market rates that have been derived through a sampling of parking charges in the vicinity of the Mobility Hub destination locations. With the exception of the Union Station Mobility Hub, located in Downtown Toronto, the densest of the origin-destination locations analyzed, parking is available free of charge in the areas surrounding the Mobility Hubs. Table 16 summarizes the parking charges used for each destination location.

A.7 FUEL COST (C_{fuel})

Fuel cost for a given trip is calculated as a function of the distance traveled, the price of fuel, and the fuel economy of the vehicle given the type of driving that is being done (either city of highway driving). For trips that involve predominantly highway driving, there is still some distance driven on city streets in order to access highway facilities. As such, fuel consumption must be calculated separately for each type of driving prior to its conversion into a monetary value. Based on an analysis of 2017 manufacturer reported fuel consumption data, made publically available by Natural Resources Canada (NRCAN), average fuel consumption for highway driving across all vehicle types is approximately 9 L/100km, while the average fuel consumption for city driving across all vehicle types is approximately 12.5 L/100km (NRCAN, 2017). The cost of fuel in the Toronto area from November 2016 to March 2017 averaged at 106.86 cents per litre (Statistics Canada, 2017). In addition to being a core variable of auto generalized cost calculations, fuel cost is also included in the generalized cost calculations for transit trips where the access or egress legs of a trip are completed by auto.

Equation 11 - Fuel Cost (c_{fuel})

$$C_{fuel} = (D_c n_c + D_h n_h)\, p$$

Where:

$D = Distance\ Travelled\ (km)$

$n = Fuel\ Economy\ \left(\frac{L}{km}\right)$

$c = city\ driving$

$h = highway\ driving$

$$p = Fuel\ Price\ \left(\frac{\$}{L}\right)$$

Table 17 - Fuel Cost Assumptions

Variable		**Assumption**
Fuel Economy (city driving)	n_c	12.5L/100km
Fuel Economy (highway)	n_h	9L / 100km
Average Fuel Price	p	106.86¢

A.8 FARE CHARGE (C_{fare})

The fare structure in the GTHA is quite complicated as it involves nine local transit operators and a regional operator. Each agency has its own set of fare policies and different transfer agreements with operators in neighbouring municipalities. For example, GO Transit, the regional rail and bus operator, offers a co-fare discount to passengers who transfer between its services and services provided by the other local transit operators, with the exception of the Toronto Transit Commission. In other parts of the region, transit operators allow passengers transferring from neighbouring transit services to board for free using a proof-of-purchase or transfer. Table 18 provides an overview of the fares and transfer costs associated with each transit operator in the region.

Table 18 - Fare Schedule for Services in the GTHA

Service Provider		**Fares**					**Cross Agency Transfers**											
		Presto	**Cash**	**Monthly Pass**	**Express**	**Zone Transfer**	**GO Co-fare**	**GO Co-Fare Discount**	**To TTC**	**To YRT**	**To MT**	**To BT**	**To OT**	**To BUT**	**To HSR**	**To DRT**	**To MIL**
Toronto Transit Commission	TTC	$2.90	$3.25	$146.25	n/a	n/a	n/a	n/a	$ -	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
York Region Transit	YRT	$3.50	$4.00	$140.00	$0.50	$1.00	$0.75	$(2.75)	n/a	$ -	$ -	$ -	n/a	n/a	n/a	$ -	n/a
Mississauga Transit	MT	$3.00	$3.50	$130.00	n/a	n/a	$0.80	$(2.20)	n/a	$ -	$ -	$ -	$ -	$ -	$ -	n/a	n/a
Brampton Transit	BT	$2.95	$3.75	$122.00	n/a	n/a	$0.80	$(2.15)	n/a	$ -	$ -	$ -	$ -	$ -	$ -	n/a	n/a
Oakville Transit	OT	$2.95	$3.75	$120.00	n/a	n/a	$0.75	$(2.20)	n/a	n/a	$ -	$ -	$ -	$ -	$ -	n/a	n/a
Burlington Transit	BUT	$2.70	$3.50	$97.00	n/a	n/a	$0.70	$(2.00)	n/a	n/a	n/a	n/a	$ -	$ -	$ -	n/a	n/a
Hamilton Street Railway	HSR	$2.30	$3.00	$101.20	n/a	n/a	$0.60	$(1.70)	n/a	n/a	n/a	n/a	$ -	$ -	$ -	n/a	n/a
Durham Region Transit	DRT	$3.05	$3.75	$115.00	n/a	n/a	$0.75	$(2.30)	n/a	$ -	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Milton Transit	MIL	n/a	$3.50	$77.00	n/a	n/a	$0.70	$(2.80)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
GO Transit	GO	$ -	$ -	$ -	$ -	$ -	$ -	$ -	n/a	$0.75	$0.80	$0.80	$0.75	$0.70	$0.60	$0.75	$0.70

A.9 TOLL CHARGE (C_{toll})

Toll charges can be calculated in a number of different ways depending on the fee structure set by the facility operator. Within the study area of the GTHA, there currently exists only one tolled facility, the 407 ETR (Express Toll Route). Fees on this facility vary by period (of the day and week), zone, and direction. In addition to a $1.00 per trip fee, a distance-based toll is charged at a rate of 22.48¢ to 44.74¢ depending on the conditions. Since a given trip can span multiple zones, more than one toll rate may apply to a given trip. Equation __ describes the toll charge calculation for the 407 ETR.

Equation 12 - Toll Charge (c_{toll})

$$C_{toll} = f(toll\ fee\ structure, distance\ traveled)$$

$$C_{toll} = \left(\sum_{i=z} D_{t,z} \cdot T_{p,z,b}\right) + T_{base}$$

Where:

$D_t = Distance\ travelled\ within\ tolled\ facility\ (km)$

$T = Toll\ Charge\ \left(\frac{\$}{km}\right)$

$T_{base} = Base\ Toll\ Charge\ (\$1.00)$

$p = period\ of\ time$

$z = zone$

$b = direction\ of\ travel$

In addition to the pay-by-usage charges applied to each trip, 407 ETR also collects a transponder lease fee that can be paid either on a monthly ($3.90/month) or annual ($23.50/year) basis, with discounts on additional transponders attached to an account. However, since this fee is paid independent of usage, and is also fairly nominal when spread across multiple trips, it is unlikely to have significant impact on the daily travel decision making process. As such, it has not been included into the calculation for toll charge (C_{toll}). Further to this, 407 ETR also offers a Rewards Program which provides incentives such as free weekend usage credits and gas savings to users who, on average, use the 407 ETR for more than 400 km a month. The effect of this incentivization program has not been directly captured within the toll charge calculation. Details on the 407ETR toll rates and zone boundaries is shown in Table 19 and Figure 40 respectively.

Table 19 - Toll Charges for 407 ETR

		Peak Period (AM)	Peak Hours (AM)	Peak Period (PM)	Peak Hours (PM)	Weekday Midday	Weekend Midday	Off Peak
		Mon-Fri: 6am-7am, 9am-10am	Mon-Fri: 7am-9am	Mon-Fri: 2:30pm-4pm, 6pm-7pm	Mon-Fri: 4pm-6pm	Weekdays 10am-2:30pm	Weekends & Holidays 11am-7pm	Weekdays 7pm-6am, Weekends & Holidays 7pm-11am
Zone 1	EB	35.97¢	42.42¢	35.95¢	40.85¢	30.88¢	28.29¢	22.48¢
(per km)	WB	34.65¢	39.42¢	37.32¢	44.74¢	30.88¢	28.29¢	22.48¢
Zone 2	EB	35.97¢	42.42¢	37.32¢	44.74¢	30.88¢	28.29¢	22.48¢
(per km)	WB	35.97¢	40.92¢	37.32¢	42.40¢	30.88¢	28.29¢	22.48¢
Zone 3	EB	34.65¢	39.42¢	37.32¢	44.74¢	30.88¢	28.29¢	22.48¢
(per km)	WB	35.97¢	42.42¢	35.95¢	40.85¢	30.88¢	28.29¢	22.48¢
Highway 407 (east of Brock Road) and Highway 412 (per km)		29.00¢	29.00¢	29.00¢	29.00¢	23.00¢	22.00¢	19.00¢

Figure 40 - Map of 407 ETR Toll Zones

A.10 MODEL COEFFICIENTS (β_n)

Coefficients within the generalized cost function provide a mechanism for adjusting the relative weights of different travel time and cost variables according to how travellers perceive various aspects of their travel. Model coefficients are typically derived from observed travel behaviour gathered through travel surveys and distilled through statistical analysis. Travel behaviour tends to vary based on socioeconomic conditions and city size, but a review of coefficient values used across the United States conducted by the United States Environment Protection Agency found that while there are differences, the range of values used are reasonably consistent across geographies (United States Environmental Protection Agency, 2000a). As the model configuration used in this thesis is quite similar to that of the COMMUTER model, the coefficients from that model have been adopted in relative terms as a base, supplemented and validated through a review of available literature (United States Environmental Protection Agency, 2000a). Most researchers note that out-of-vehicle time is perceived by travellers to be significantly more onerous than in-vehicle travel time, many citing values within the range of 2 to 3 times that of in-vehicle travel time (Casello & Hellinga, 2008; Lesley, 2009; Small, 2012; Taylor et al., 1997; United States Environmental Protection Agency, 2000a; Wachs, 1990). Lesley makes a further differentation between wait time and walking time (access and egress), noting that wait time is perceived to be even more onerous than walking time--this finding concurs with the coefficients used in the COMMUTER model (2009). Table 20 lists out the coefficients used, presented in relative terms to the coefficient for in-vehicle travel time which has been held constant as 1.0. Out of the list of variables, access travel time, fuel cost, and toll charge were not assigned specific coefficient values within the COMMUTER model, so values from other variables have been taken as a proxy.

Table 20 - Generalized Cost Variable Coefficients

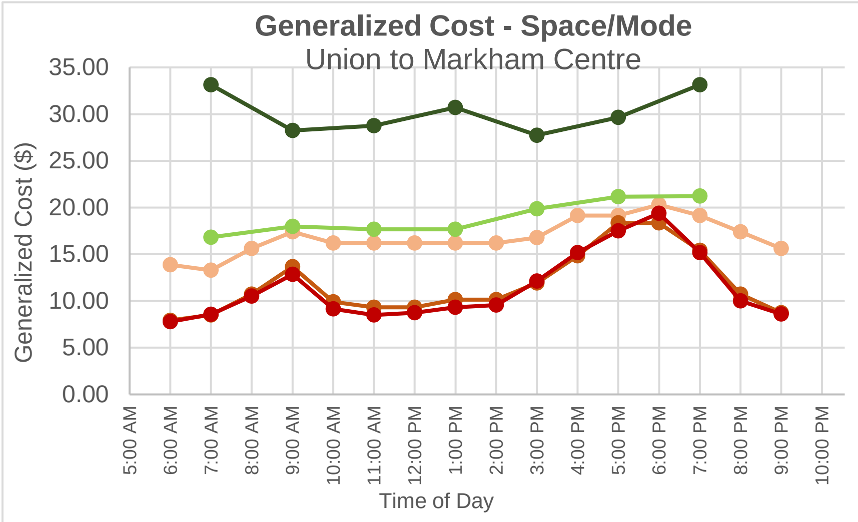
Variable		**Value of Coefficient**	
Access Travel Time	t_{access}	β_{access}	1.876
Wait Time	t_{wait}	β_{wait}	2.124
In-Vehicle Travel Time	t_{IV}	β_{IV}	1.000
Egress Travel Time	t_{egress}	β_{egress}	1.876
Parking Charge	$C_{parking}$	$\beta_{parking}$	0.322
Fuel Cost	C_{fuel}	β_{fuel}	0.236
Fare Charge	C_{fare}	β_{fare}	0.236
Toll Charge	C_{toll}	β_{toll}	0.322

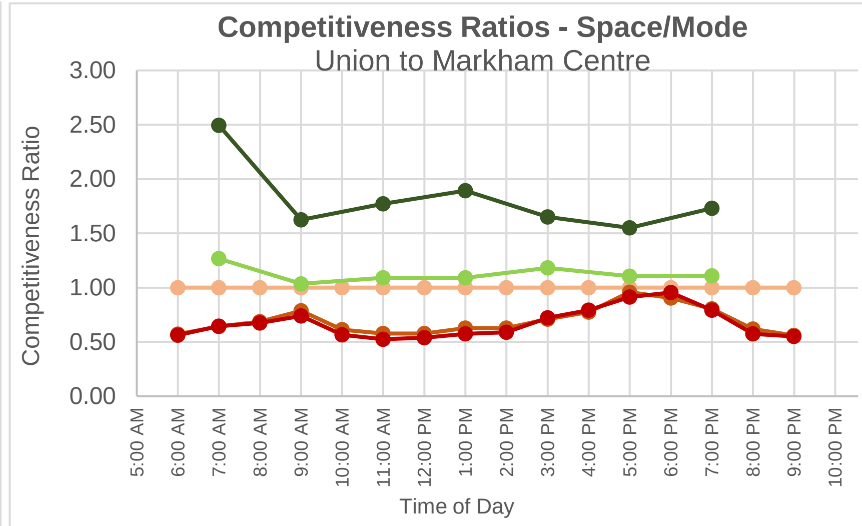
As access and egress time are typically considered together, the coefficient for egress travel time has been adopted as a proxy for access travel time coefficient. By a similar logic, the coefficients for parking charge and fare charge have been adopted for toll charge and fuel cost correspondingly. In the same way that fares are fundamental transit, fuel is an out-of-pocket cost that is fundamental to every trip made by auto and is somewhat internalized into the decision to drive. Tolls on the other hand are limited to select trips and is a charge that travellers have to make an active decision to pay. Although parking charges and toll charges are not directly comparable, the parking charge coefficient is on the higher end of the scale for out-of-pocket cost coefficients, which would rightly characterize the more onerous nature of tolls. Such approximations should serve the purposes of this thesis as the model used is intended strictly as a proof-of-concept. In practice, model coefficients should be re-calibrated to the local context using empirical data.

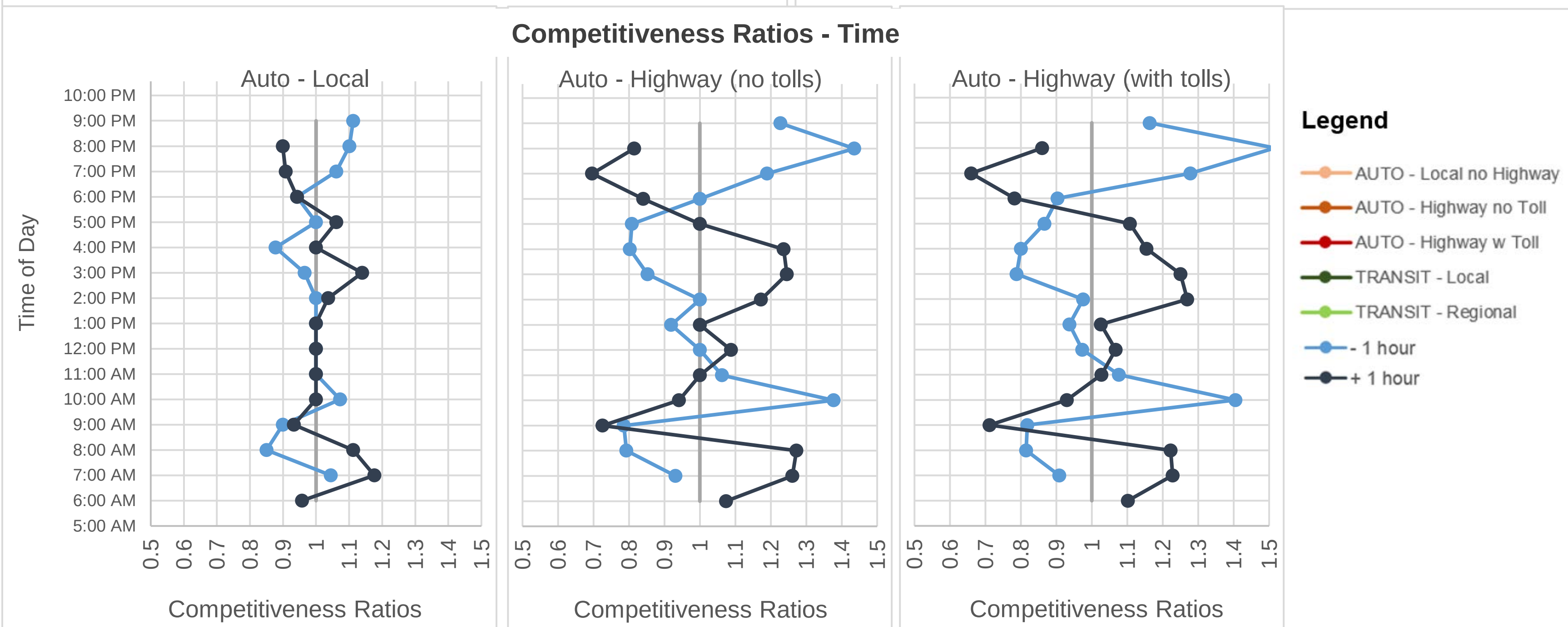
APPENDIX B – MODULE 1 RESULTS

Included in this appendix are the results of the analysis under module 1, which compared alternatives on the basis of the competitiveness ratio calculation. The following sections have been organized according to origin-destination pair. Each set includes a comparison of the generalized costs across space and mode, the competitiveness ratios across space and mode, and the competitiveness ratios across time.

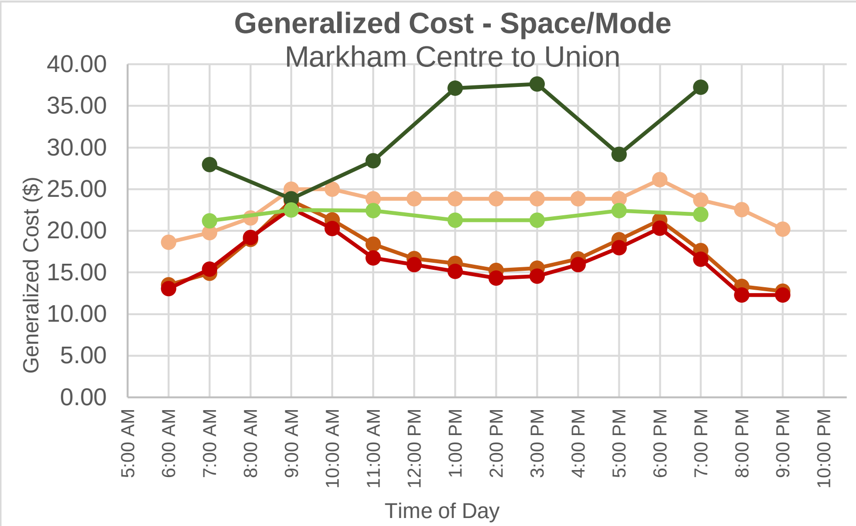
B.1 UNION TO MARKHAM CENTRE

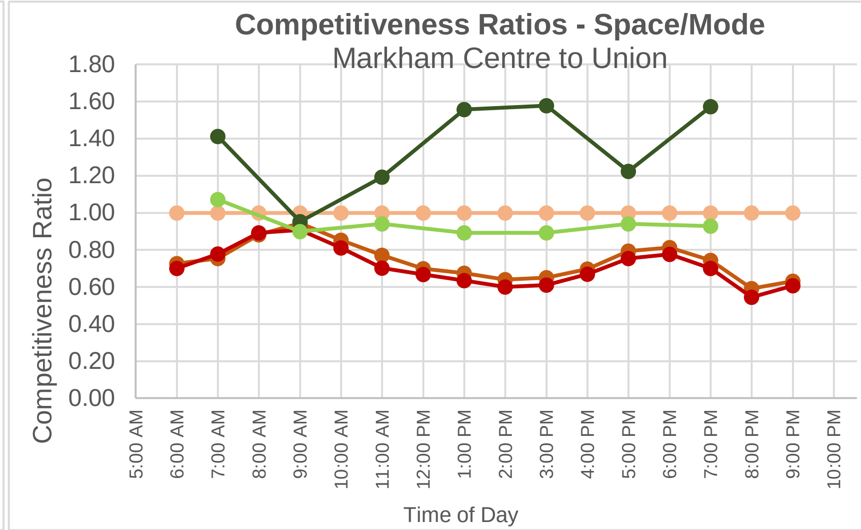


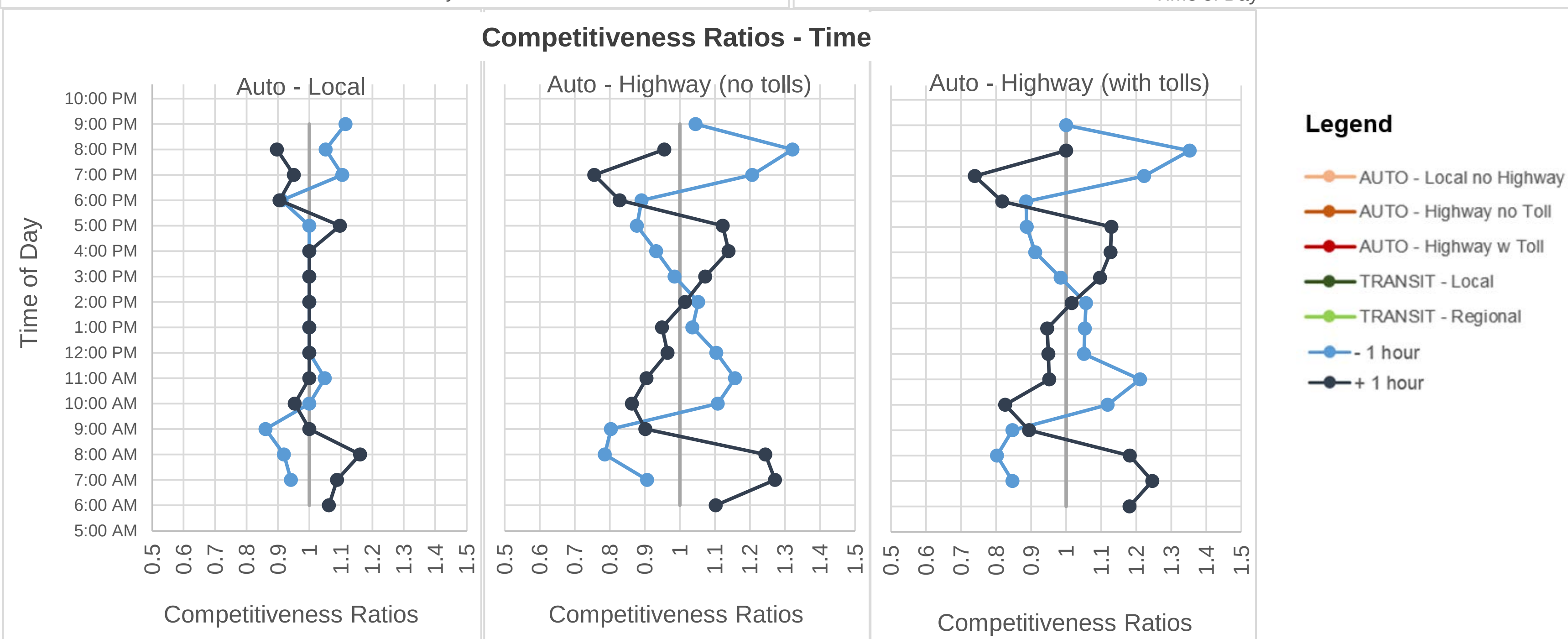




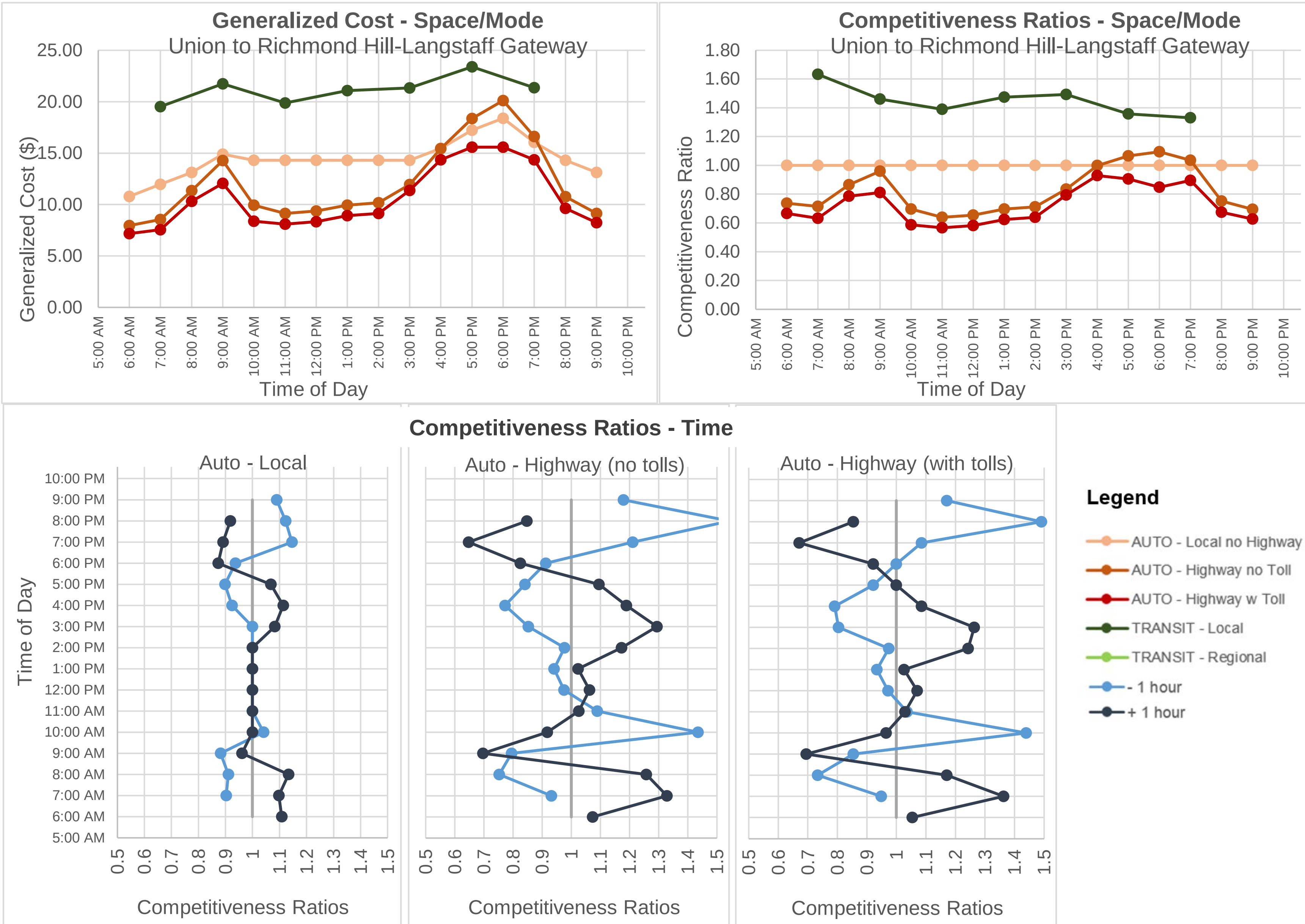
B.2 MARKHAM CENTRE TO UNION

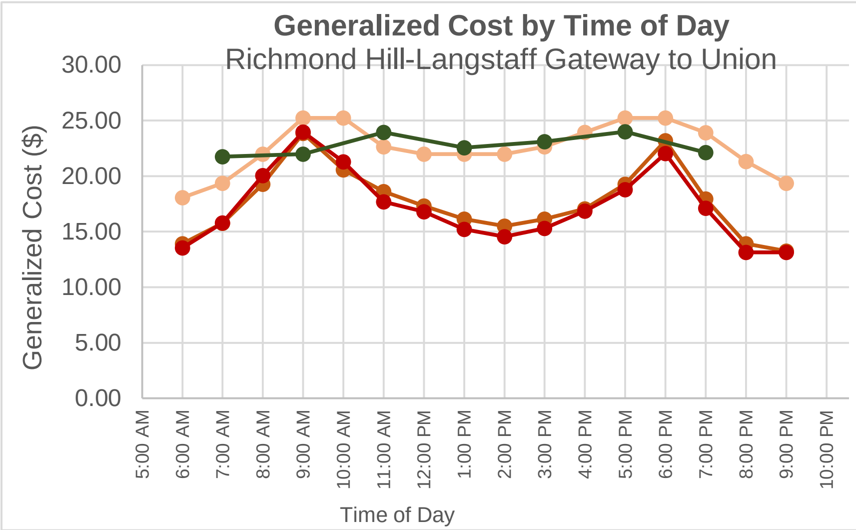






B.3 UNION TO RICHMOND HILL-LANGSTAFF GATEWAY




Generalized Cost by Time of Day
Richmond Hill-Langstaff Gateway to Union
Generalized Cost ($)
30.00
25.00
20.00
15.00
10.00
5.00
0.00
5:00 AM
6:00 AM
7:00 AM
8:00 AM
9:00 AM
10:00 AM
11:00 AM
12:00 PM
1:00 PM
2:00 PM
3:00 PM
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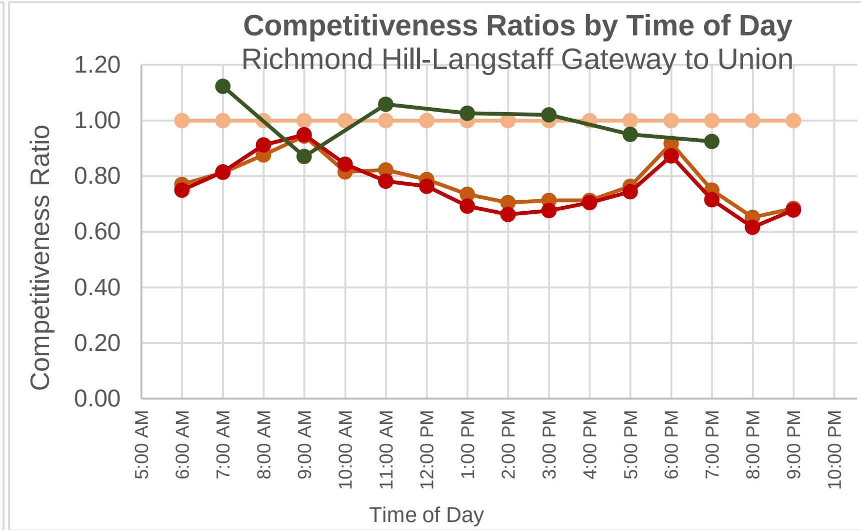
9:00 PM
10:00 PM
Time of Day


Competitiveness Ratios by Time of Day
Richmond Hill-Langstaff Gateway to Union
Competitiveness Ratio
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0.60
0.40
0.20
0.00
5:00 AM
6:00 AM
7:00 AM
8:00 AM
9:00 AM
10:00 AM
11:00 AM
12:00 PM
1:00 PM
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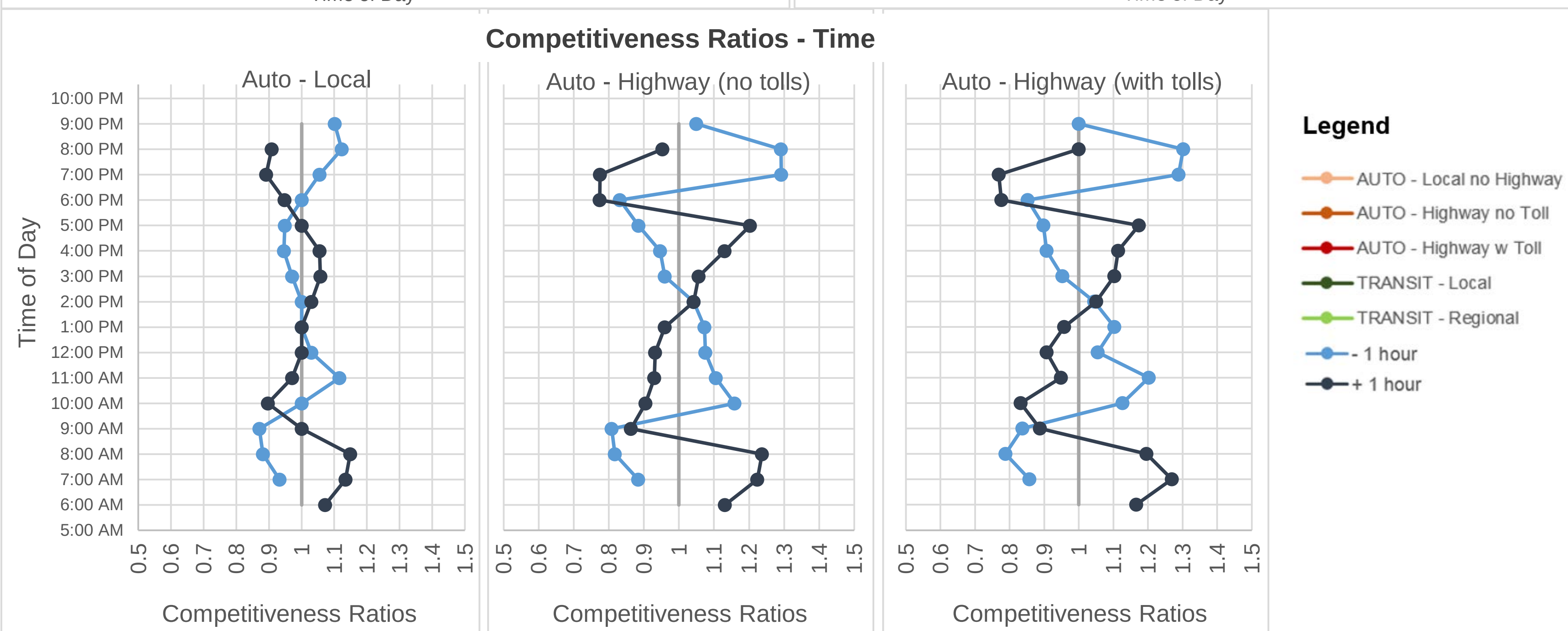
9:00 PM
10:00 PM
Time of Day


Competitiveness Ratios - Time
Auto - Local
Auto - Highway (no tolls)
Auto - Highway (with tolls)
Time of Day
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9:00 PM
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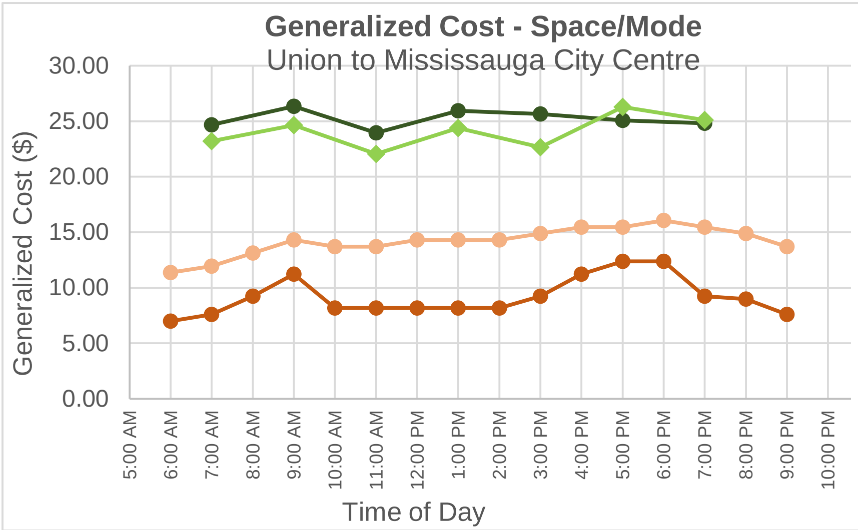
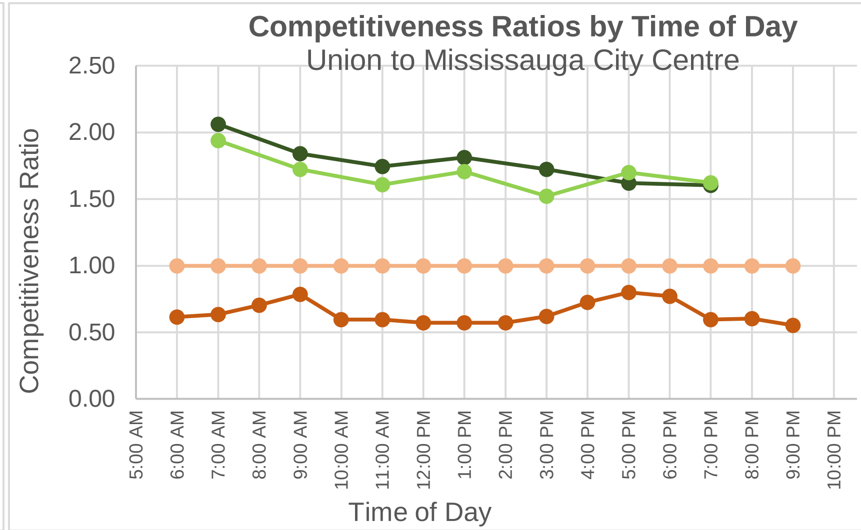
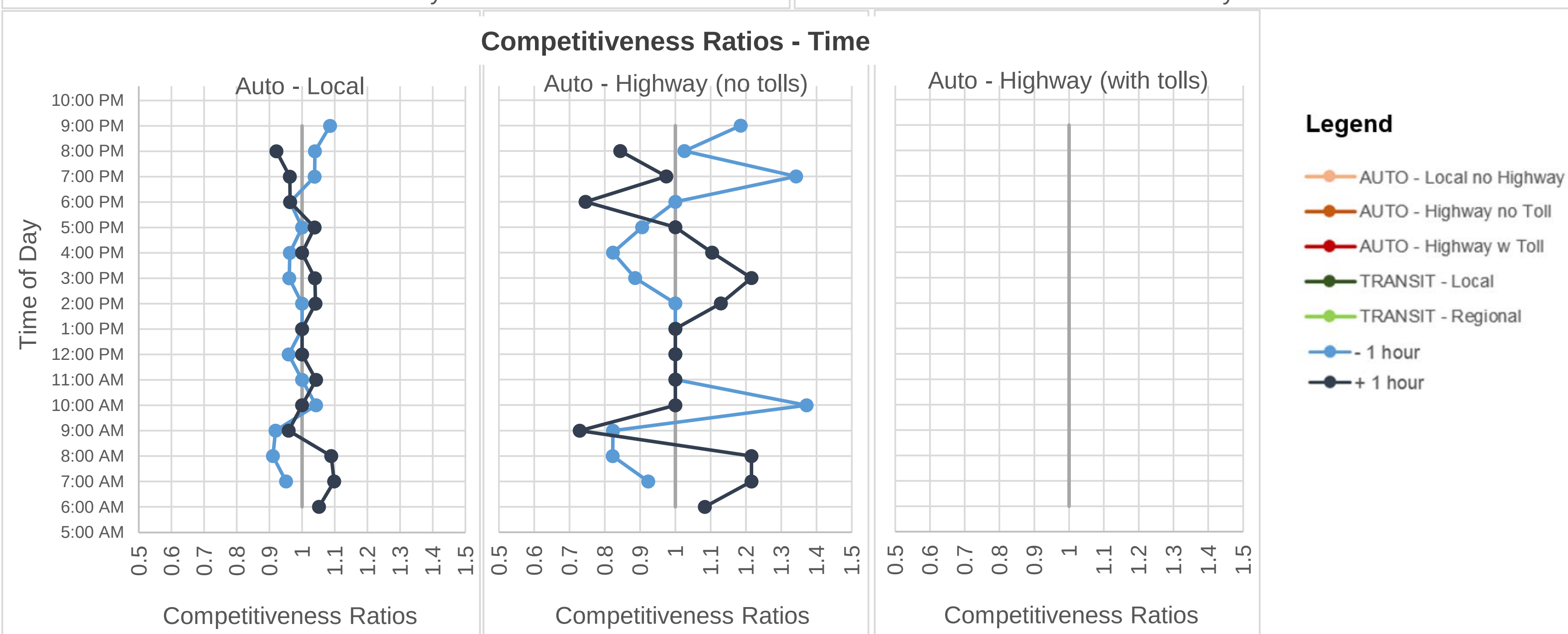
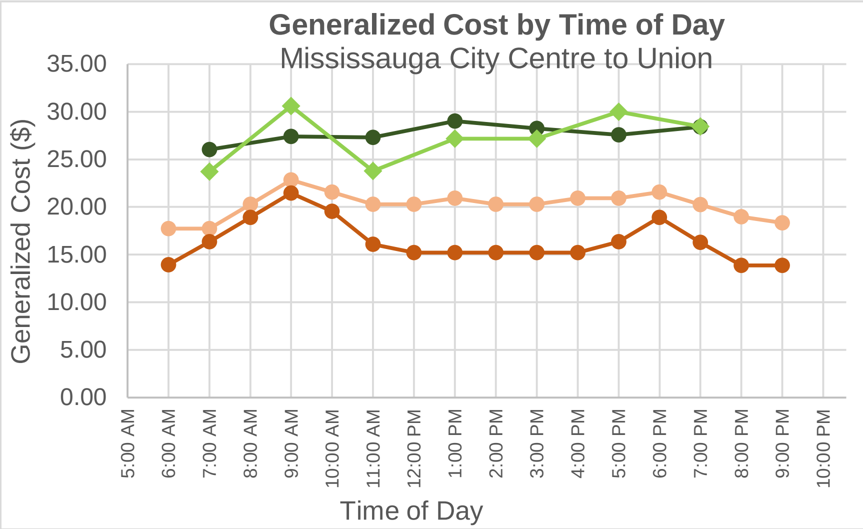
6:00 PM
5:00 PM
4:00 PM
3:00 PM
2:00 PM
1:00 PM
12:00 PM
11:00 AM
10:00 AM
9:00 AM
8:00 AM
7:00 AM
6:00 AM
5:00 AM
0.5
0.6
0.7
0.8
0.9
1
1.1
1.2
1.3
1.4
1.5
Competitiveness Ratios
Legend
AUTO - Local no Highway
AUTO - Highway no Toll
AUTO - Highway w Toll
TRANSIT - Local
TRANSIT - Regional
- 1 hour
+ 1 hour

B.5 UNION TO MISSISSAUGA CITY CENTRE








Generalized Cost by Time of Day
Mississauga City Centre to Union
Generalized Cost ($)
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30.00
25.00
20.00
15.00
10.00
5.00
0.00
5:00 AM
6:00 AM
7:00 AM
8:00 AM
9:00 AM
10:00 AM
11:00 AM
12:00 PM
1:00 PM
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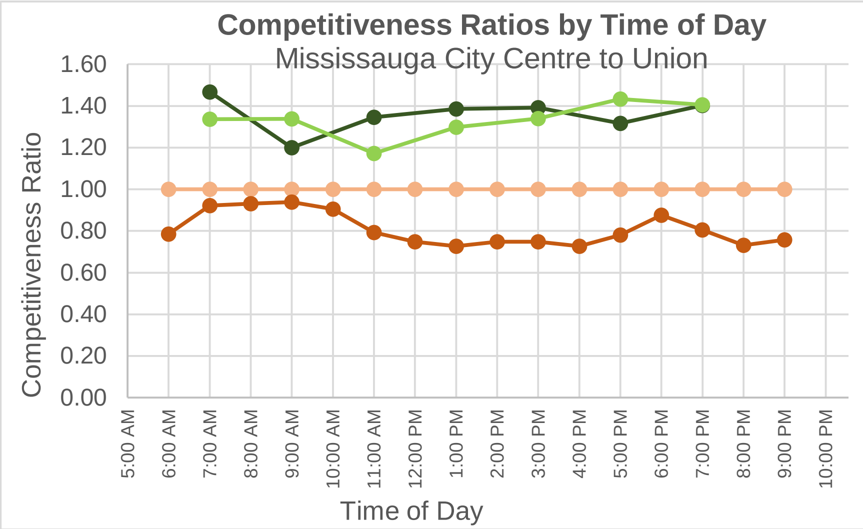
10:00 PM
Time of Day


Competitiveness Ratios by Time of Day
Mississauga City Centre to Union
Competitiveness Ratio
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1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
5:00 AM
6:00 AM
7:00 AM
8:00 AM
9:00 AM
10:00 AM
11:00 AM
12:00 PM
1:00 PM
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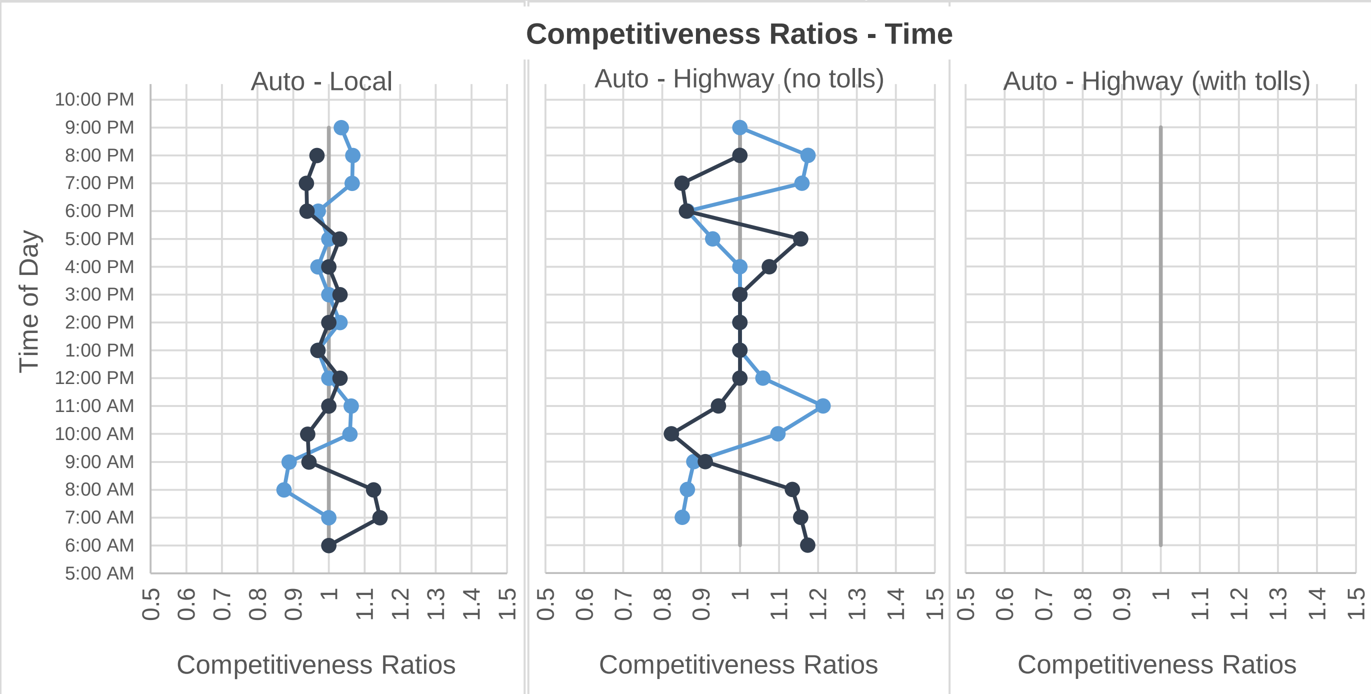
9:00 PM
10:00 PM
Time of Day


Competitiveness Ratios - Time
Auto - Local
Auto - Highway (no tolls)
Auto - Highway (with tolls)
Time of Day
10:00 PM
9:00 PM
8:00 PM
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6:00 PM
5:00 PM
4:00 PM
3:00 PM
2:00 PM
1:00 PM
12:00 PM
11:00 AM
10:00 AM
9:00 AM
8:00 AM
7:00 AM
6:00 AM
5:00 AM
0.5
0.6
0.7
0.8
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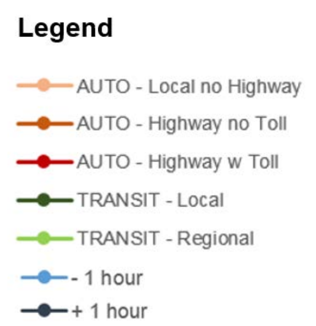
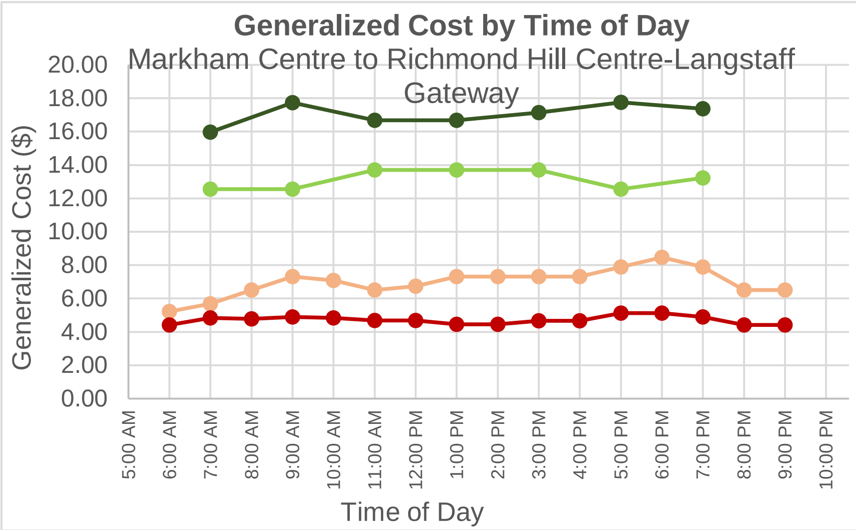
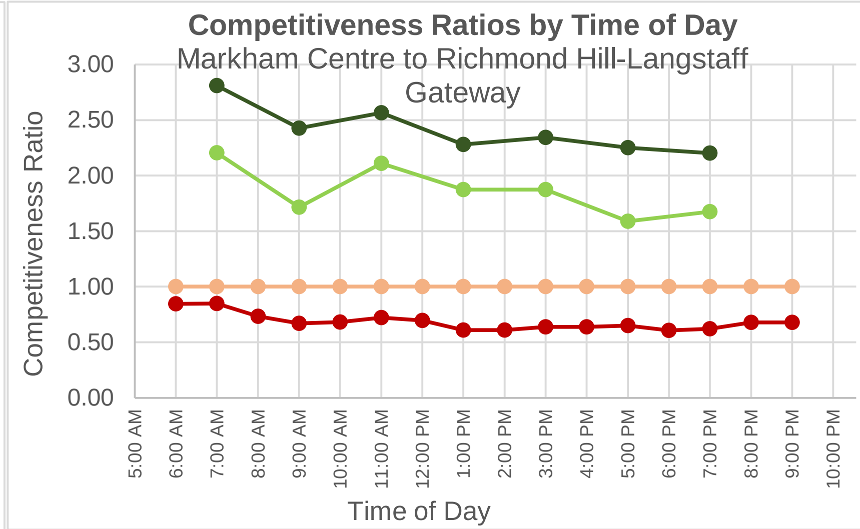
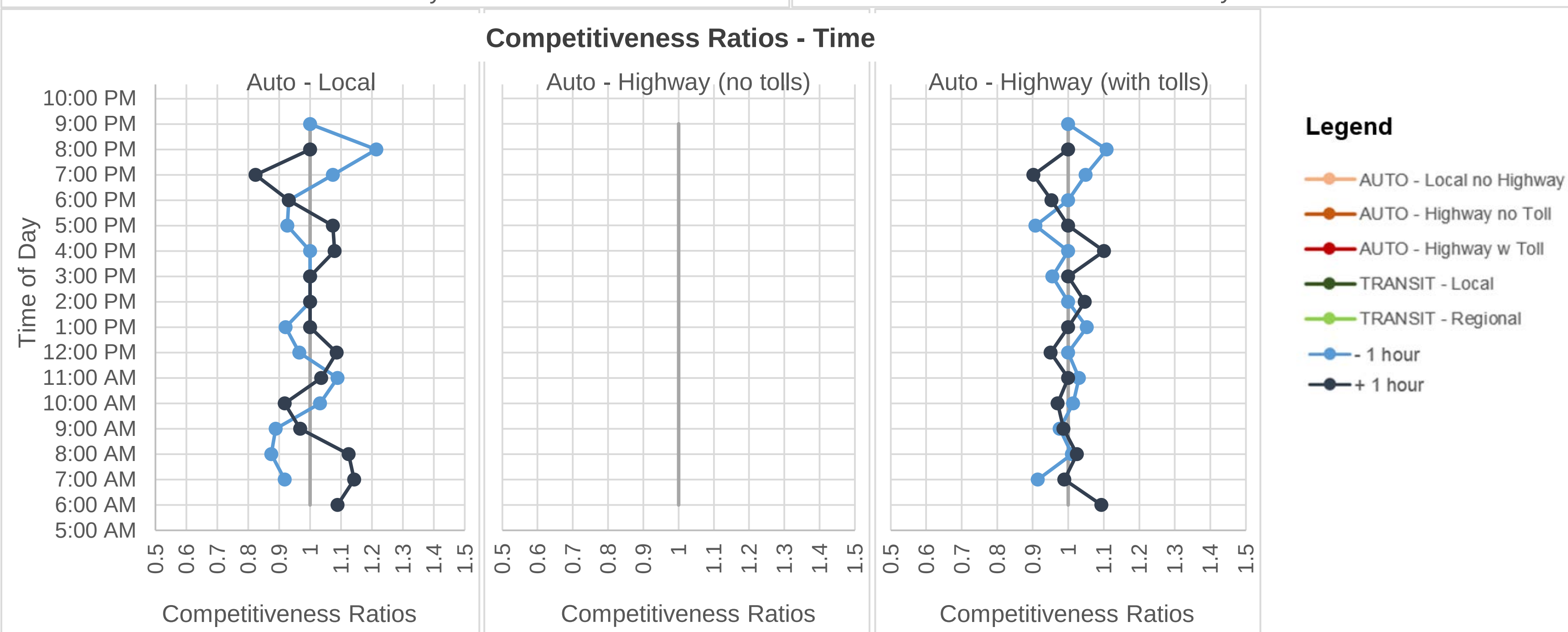
1
1.1
1.2
1.3
1.4
1.5
Competitiveness Ratios
Competitiveness Ratios
Competitiveness Ratios


Legend
AUTO - Local no Highway
AUTO - Highway no Toll
AUTO - Highway w Toll
TRANSIT - Local
TRANSIT - Regional
- 1 hour
+ 1 hour

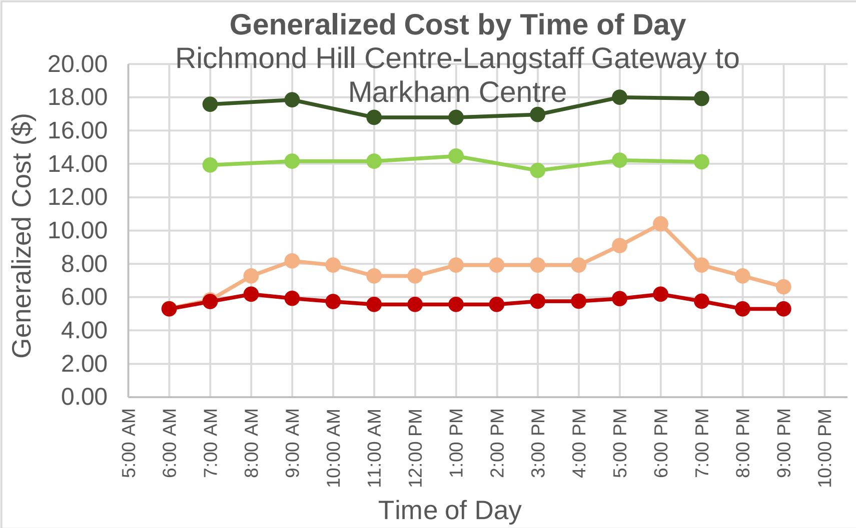
B.7 MARKHAM CENTRE TO RICHMOND HILL-LANGSTAFF GATEWAY

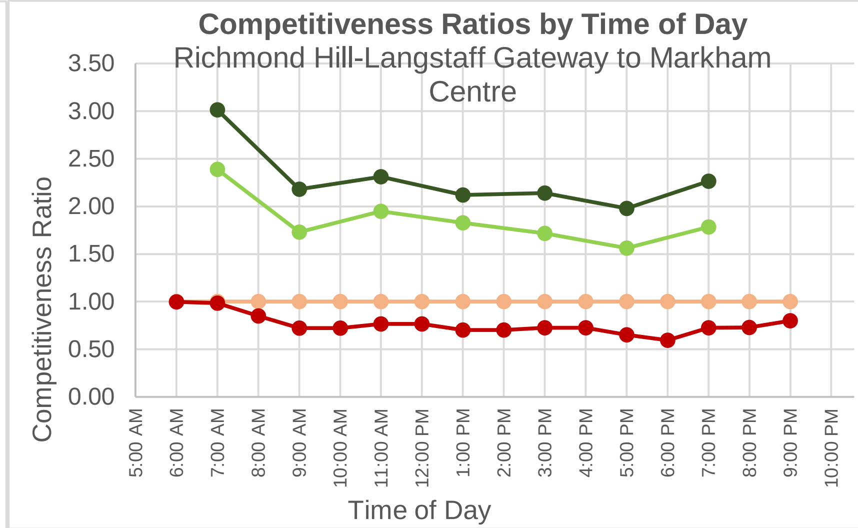


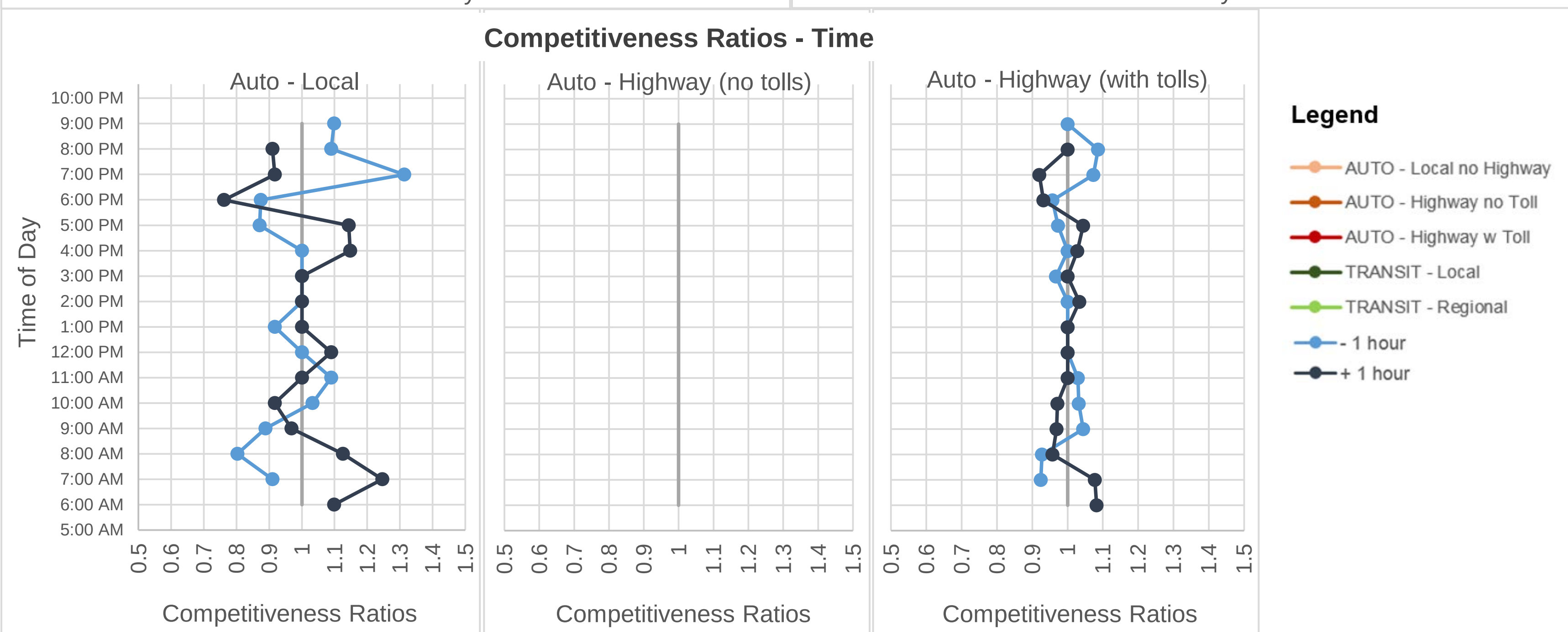




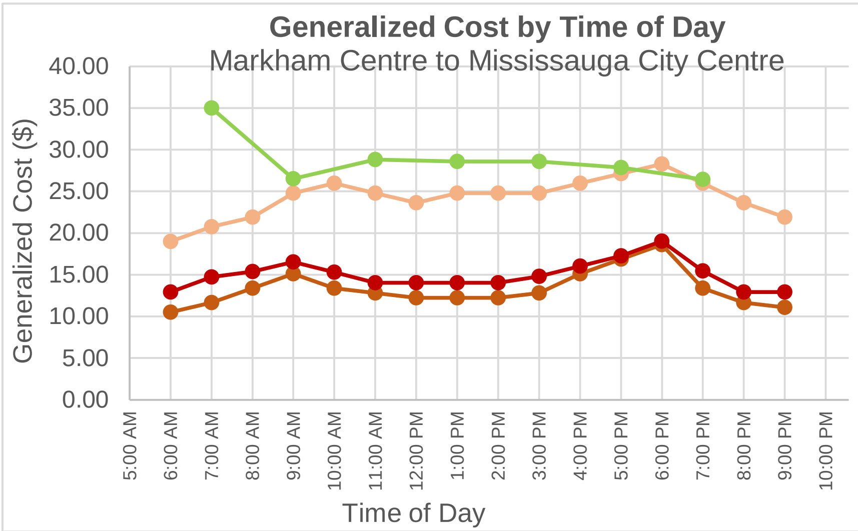
B.8 RICHMOND HILL-LANGSTAFF GATEWAY TO MARKHAM CENTRE

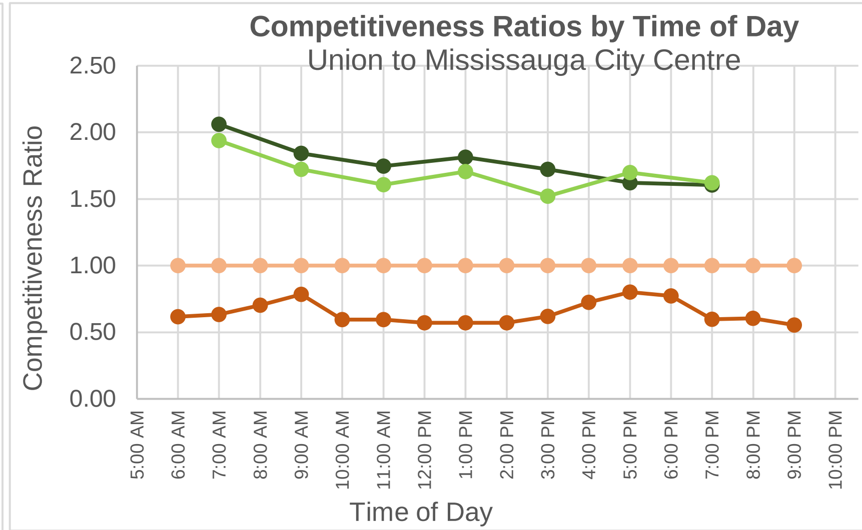


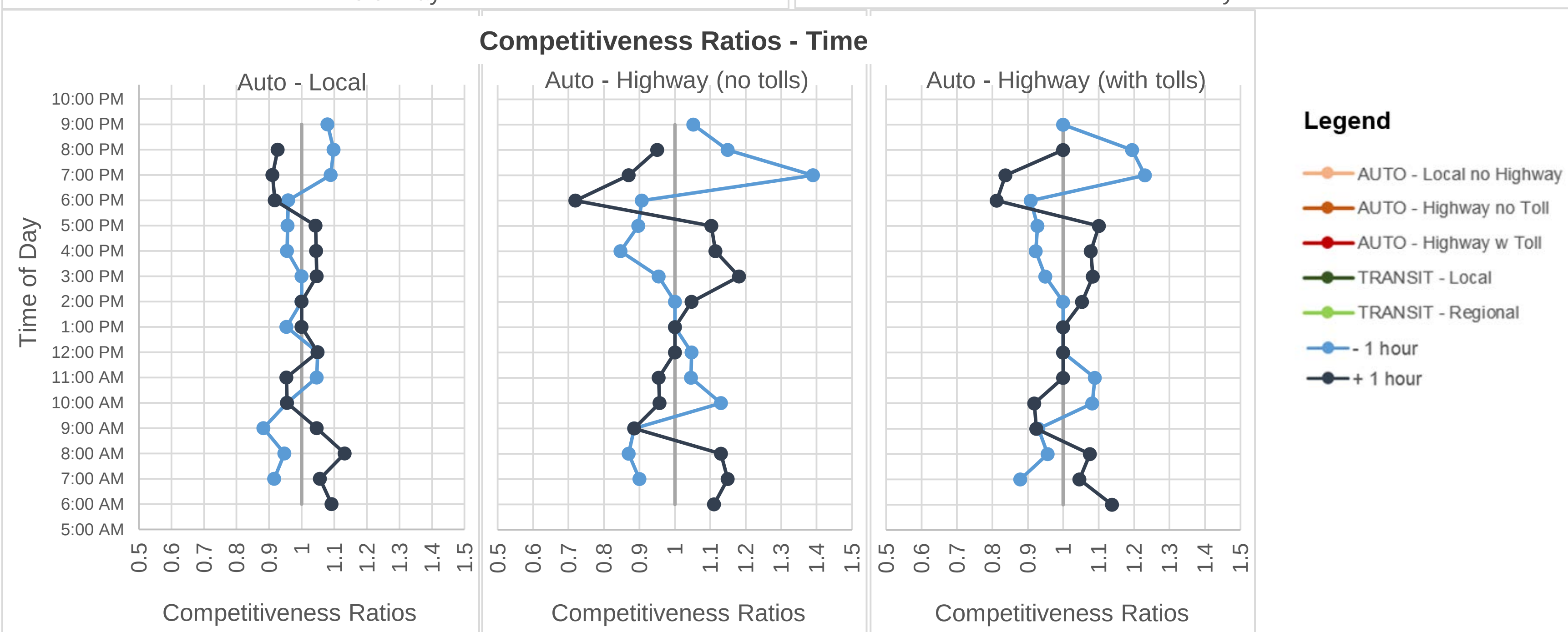


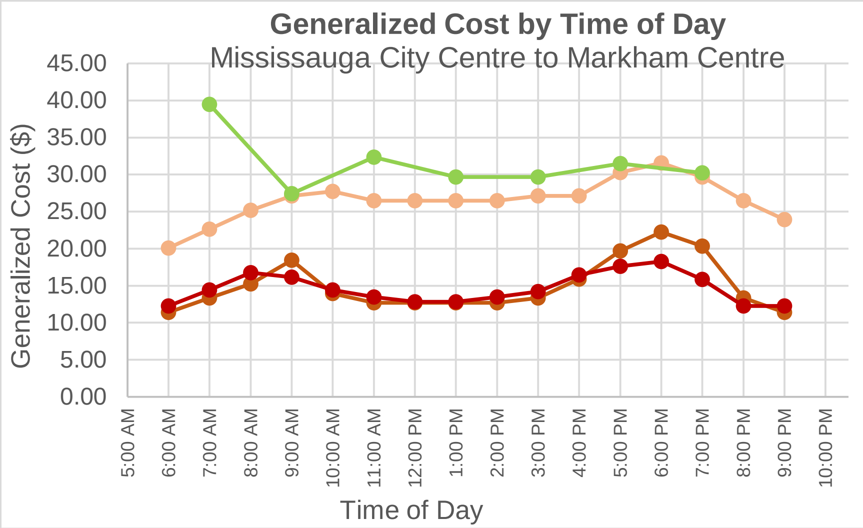


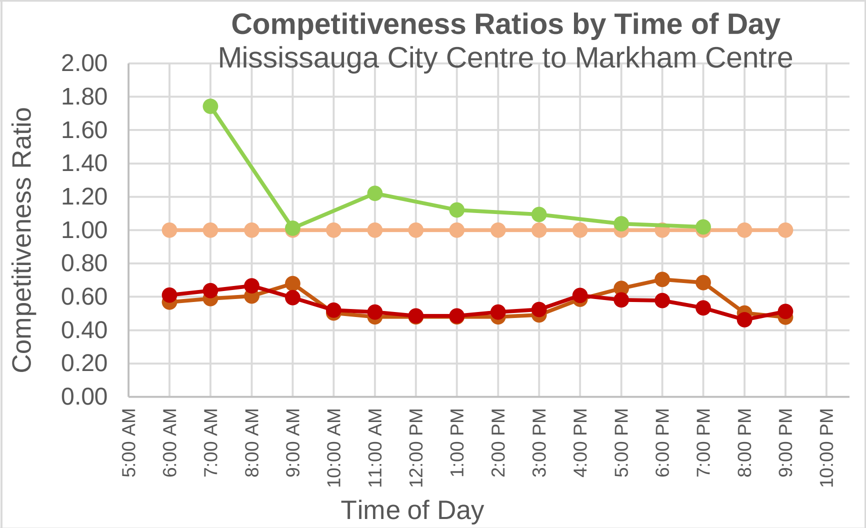
B.9 MARKHAM CENTRE TO MISSISSAUGA CITY CENTRE

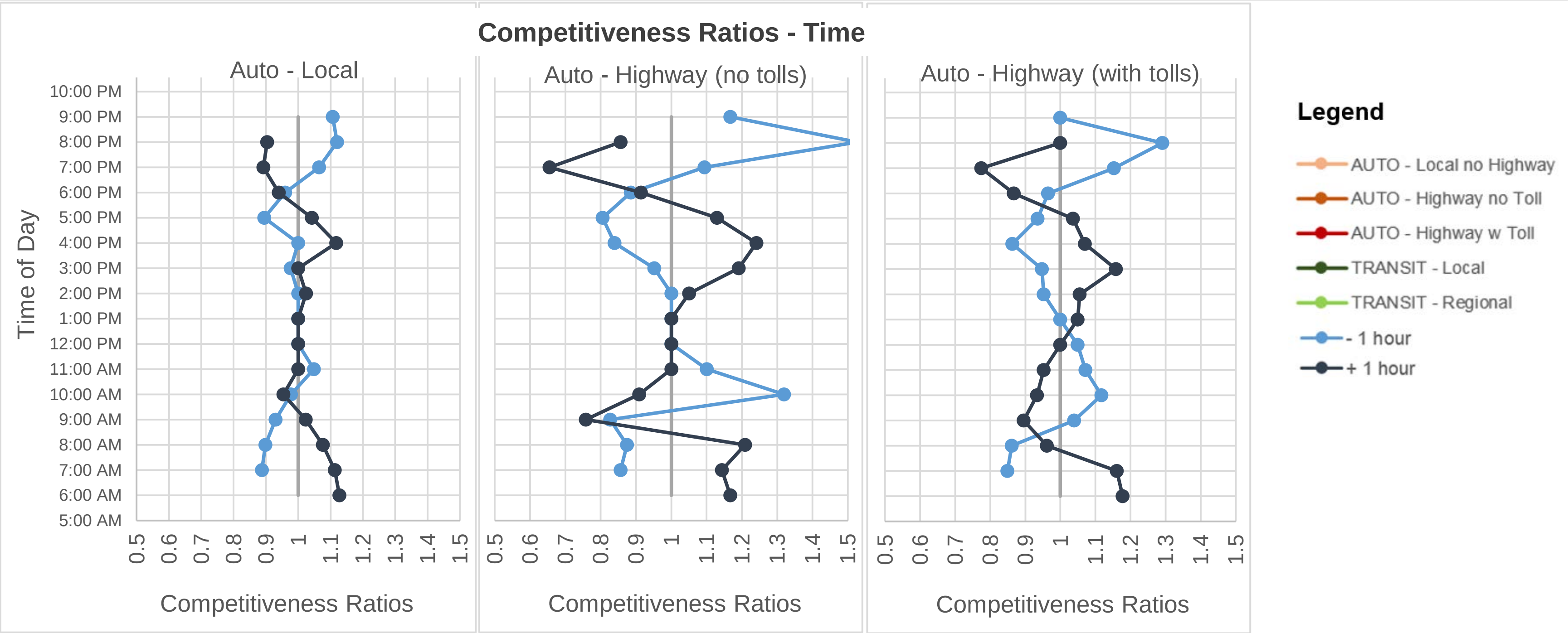




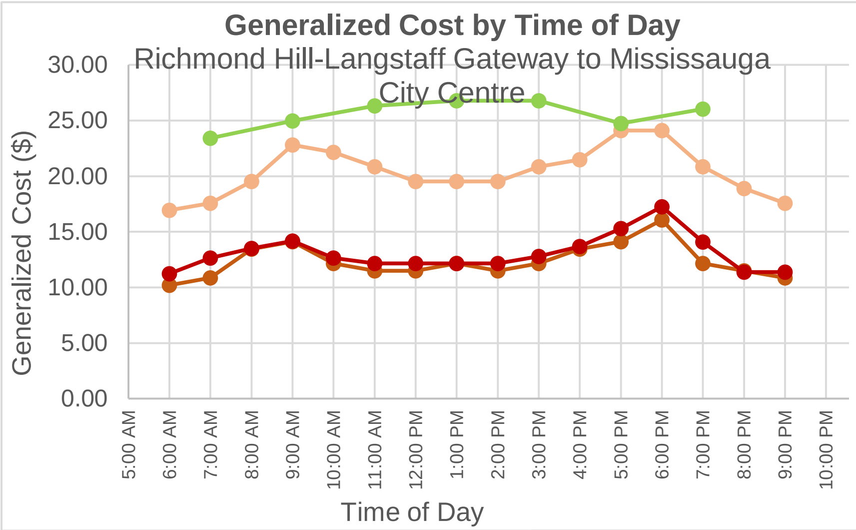


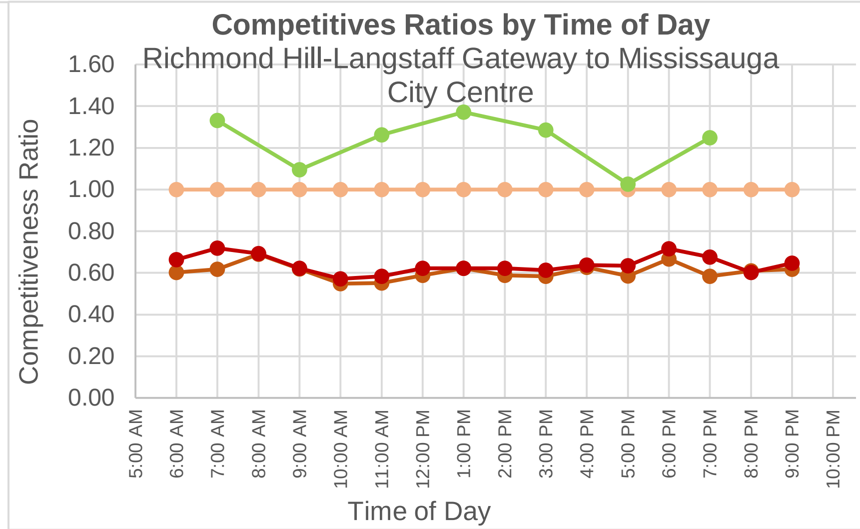

Generalized Cost by Time of Day
Mississauga City Centre to Markham Centre
Generalized Cost ($)
Time of Day

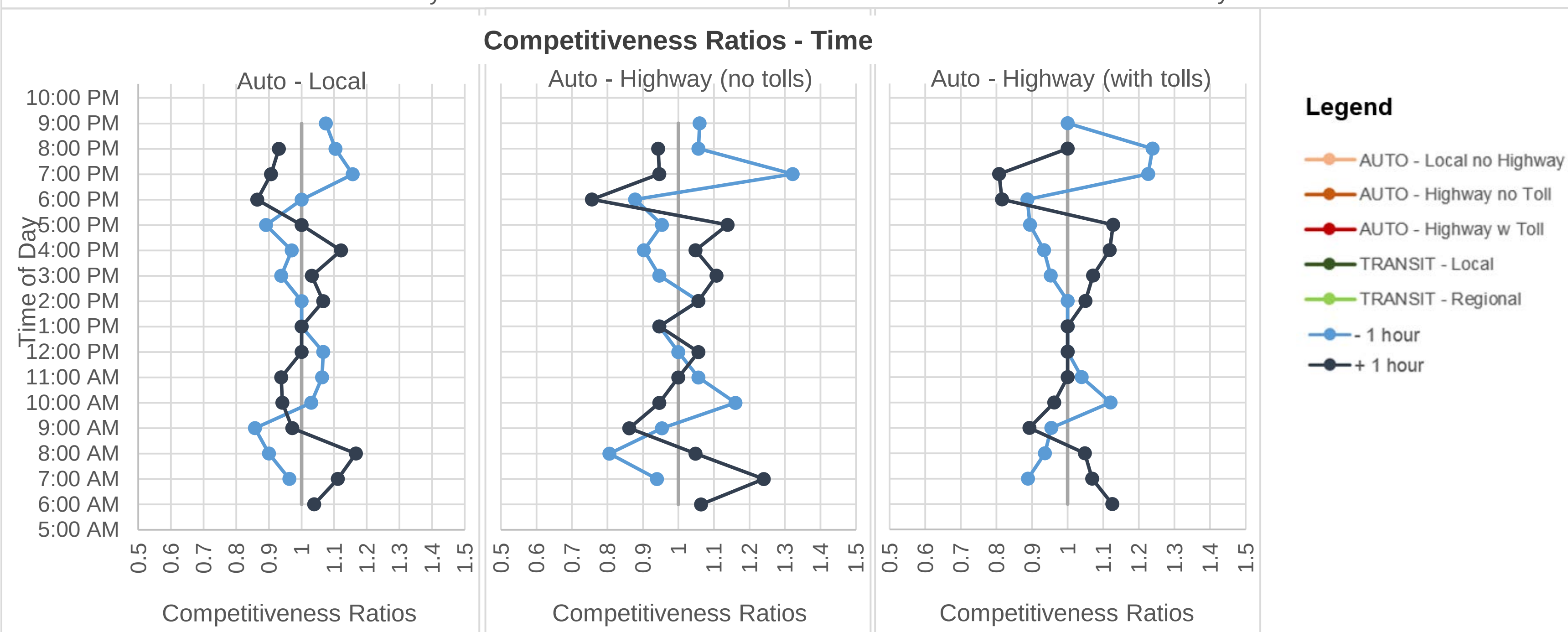

Competitiveness Ratios by Time of Day
Mississauga City Centre to Markham Centre
Competitiveness Ratio
Time of Day

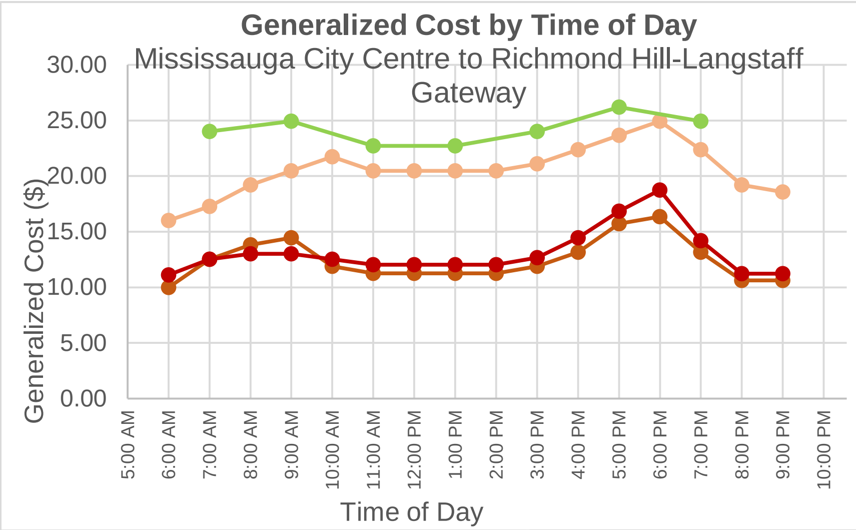

Competitiveness Ratios - Time
Auto - Local
Auto - Highway (no tolls)
Auto - Highway (with tolls)
Time of Day
Competitiveness Ratios
Legend
AUTO - Local no Highway
AUTO - Highway no Toll
AUTO - Highway w Toll
TRANSIT - Local
TRANSIT - Regional
- 1 hour
+ 1 hour

B.11 RICHMOND HILL-LANGSTAFF GATEWAY TO MISSISSAUGA CITY CENTRE








Generalized Cost by Time of Day
Mississauga City Centre to Richmond Hill-Langstaff Gateway
Generalized Cost ($)
30.00
25.00
20.00
15.00
10.00
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0.00
5:00 AM
6:00 AM
7:00 AM
8:00 AM
9:00 AM
10:00 AM
11:00 AM
12:00 PM
1:00 PM
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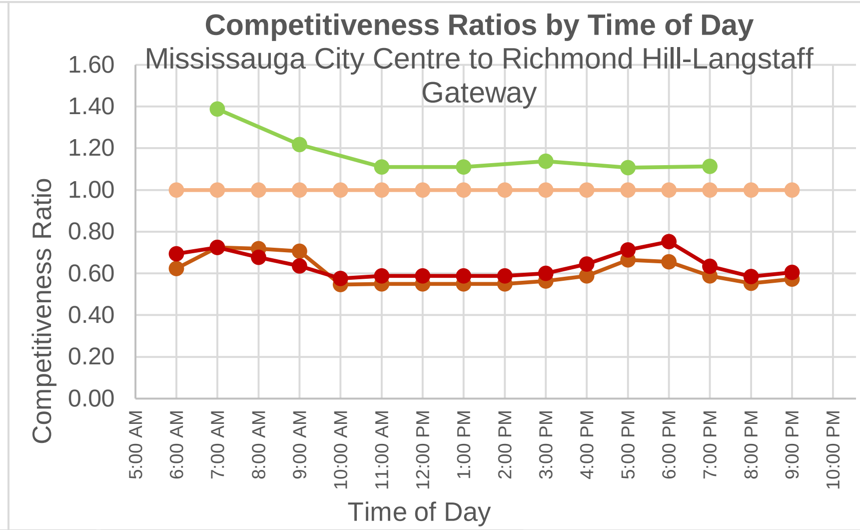
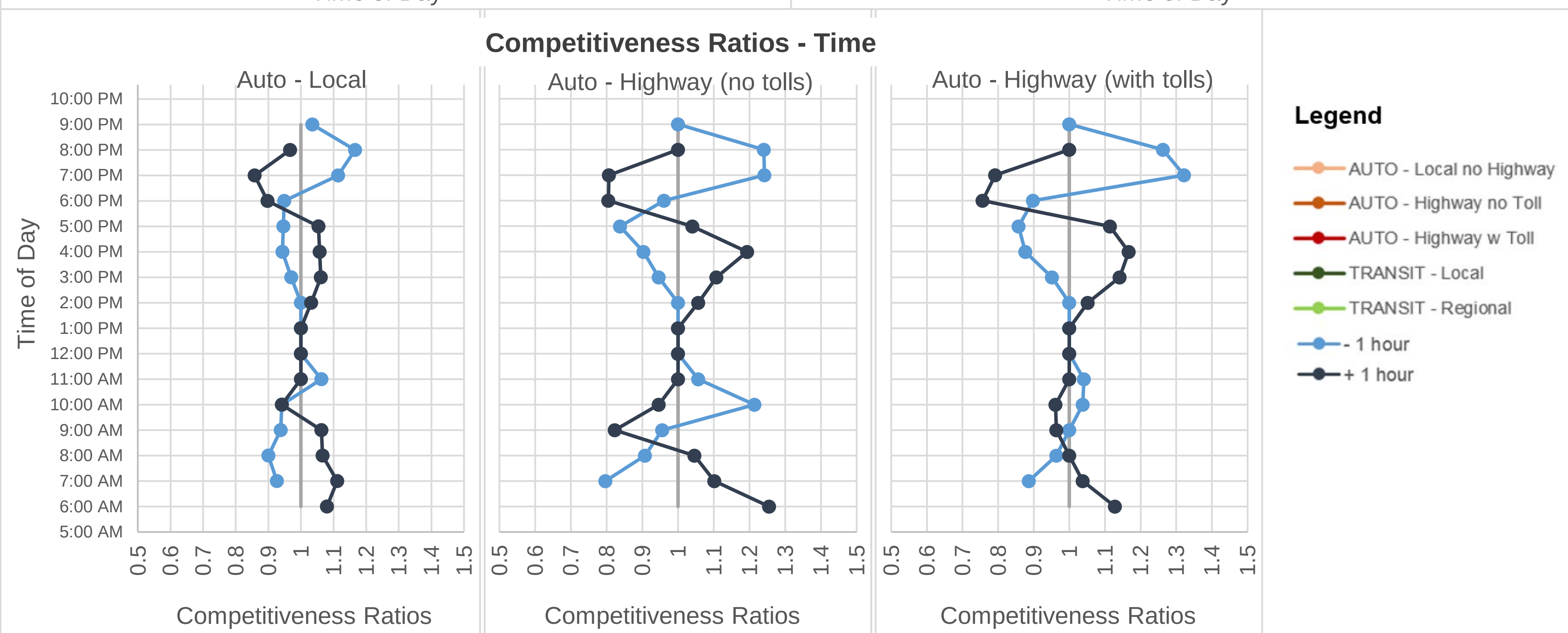
9:00 PM
10:00 PM
Time of Day


Competitiveness Ratios by Time of Day
Mississauga City Centre to Richmond Hill-Langstaff Gateway
Competitiveness Ratio
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
5:00 AM
6:00 AM
7:00 AM
8:00 AM
9:00 AM
10:00 AM
11:00 AM
12:00 PM
1:00 PM
2:00 PM
3:00 PM
4:00 PM
5:00 PM
6:00 PM
7:00 PM
8:00 PM
9:00 PM
10:00 PM
Time of Day


Competitiveness Ratios - Time
Auto - Local
Auto - Highway (no tolls)
Auto - Highway (with tolls)
Time of Day
10:00 PM
9:00 PM
8:00 PM
7:00 PM
6:00 PM
5:00 PM
4:00 PM
3:00 PM
2:00 PM
1:00 PM
12:00 PM
11:00 AM
10:00 AM
9:00 AM
8:00 AM
7:00 AM
6:00 AM
5:00 AM
0.5
0.6
0.7
0.8
0.9
1
1.1
1.2
1.3
1.4
1.5
Competitiveness Ratios
Legend
AUTO - Local no Highway
AUTO - Highway no Toll
AUTO - Highway w Toll
TRANSIT - Local
TRANSIT - Regional
- 1 hour
+ 1 hour

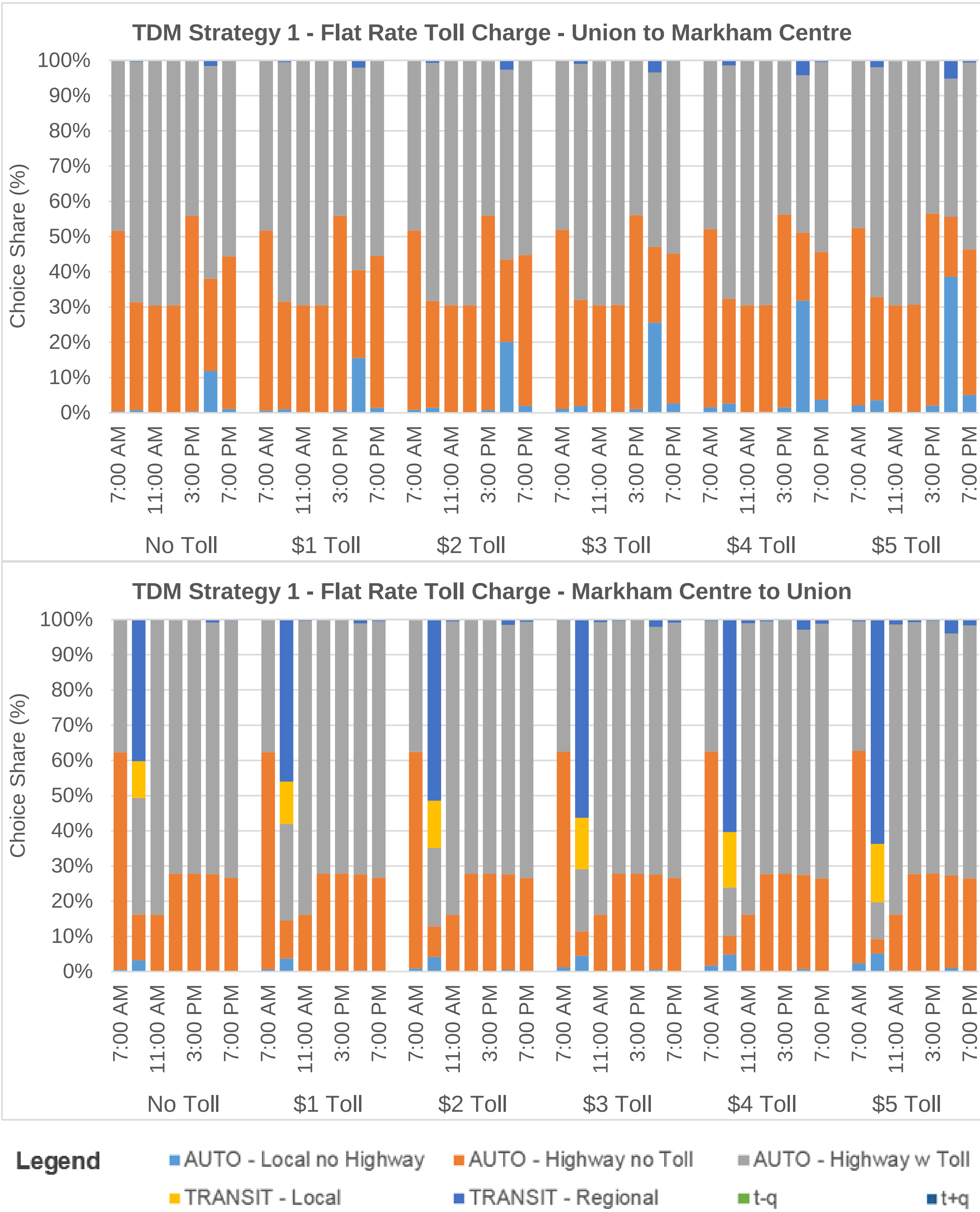
APPENDIX C – MODULE 2 RESULTS

Included in this appendix are the results of the analysis under module 2, which tested the impact of select TDM strategies on the relative attractiveness of competing alternatives across space, time, and mode. The following has been organized by the four TDM strategies tested, and then by origin-destination corridor.

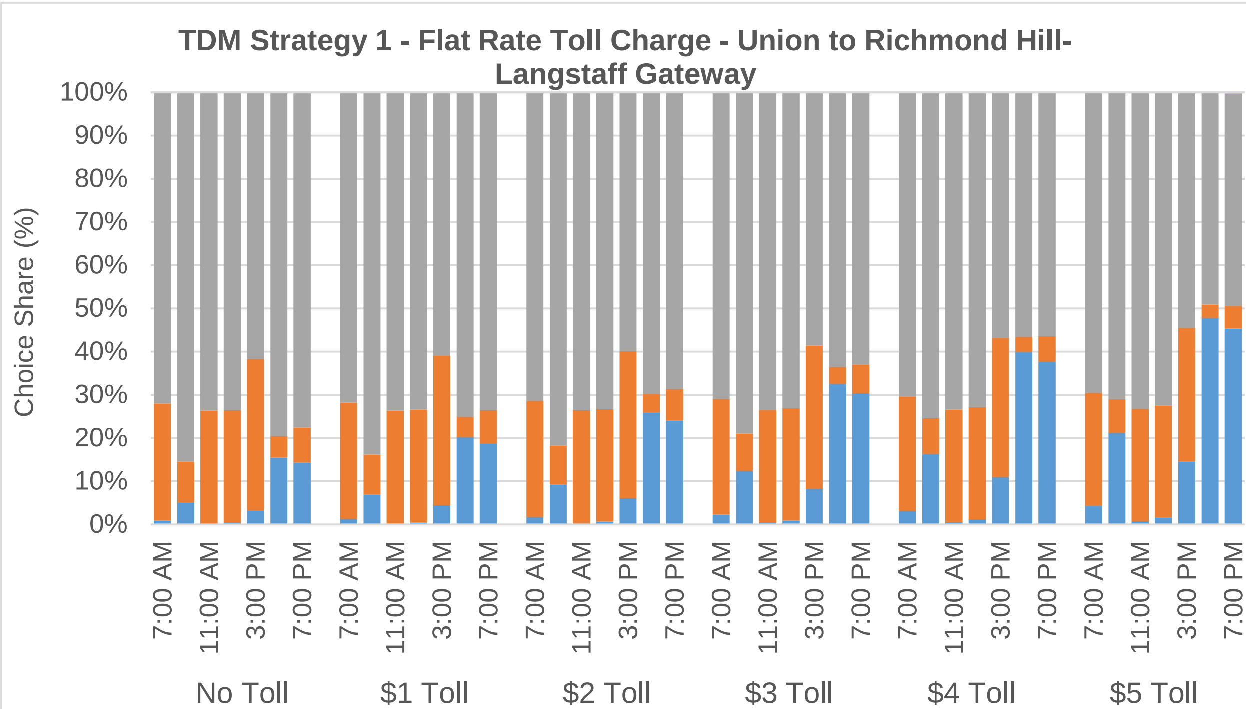
Note that results have been omitted in instances where there was insufficient data (such as in the case of transit travel in the Union & Richmond Hill-Langstaff Gateway Corridor), or where the TDM strategy did not apply (such as in the case of the Markham Centre & Richmond Hill-Langstaff where there are no other non-tolled highways for an additional toll to be applied).

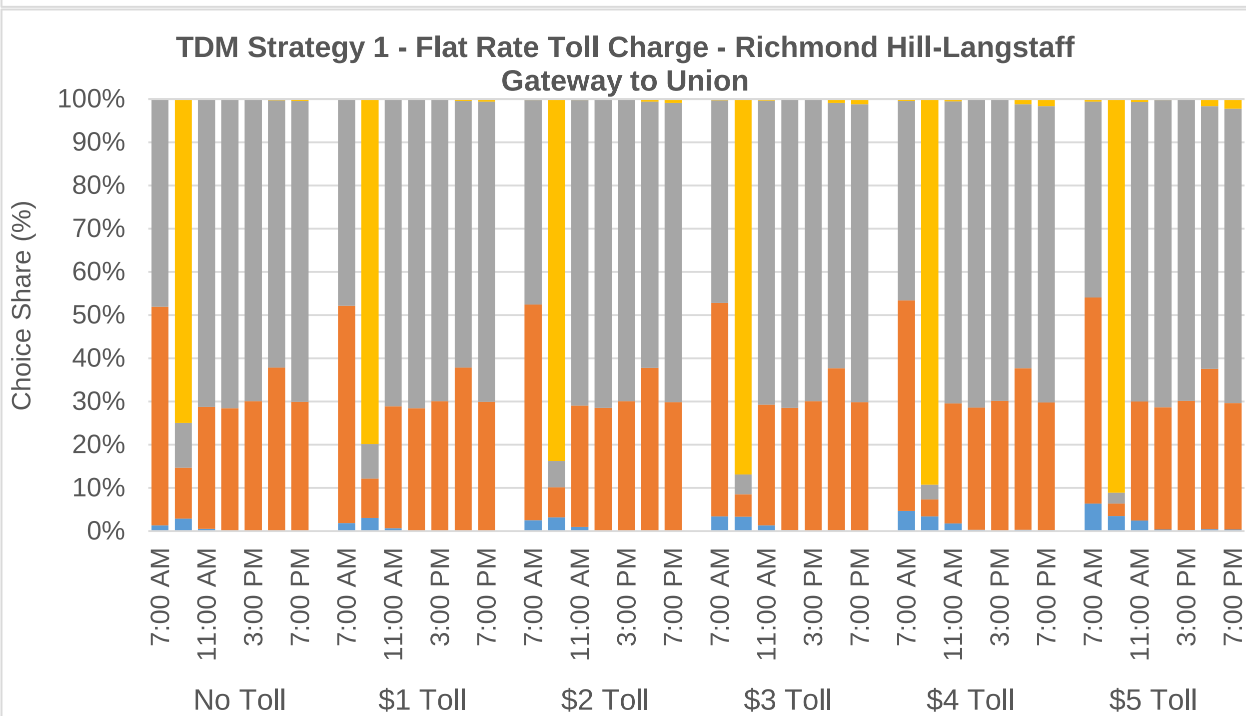
C.1 TDM STRATEGY 1 – FLAT RATE TOLL CHARGE

Union & Markham Centre Corridor



Union & Richmond Hill-Langstaff Gateway Corridor

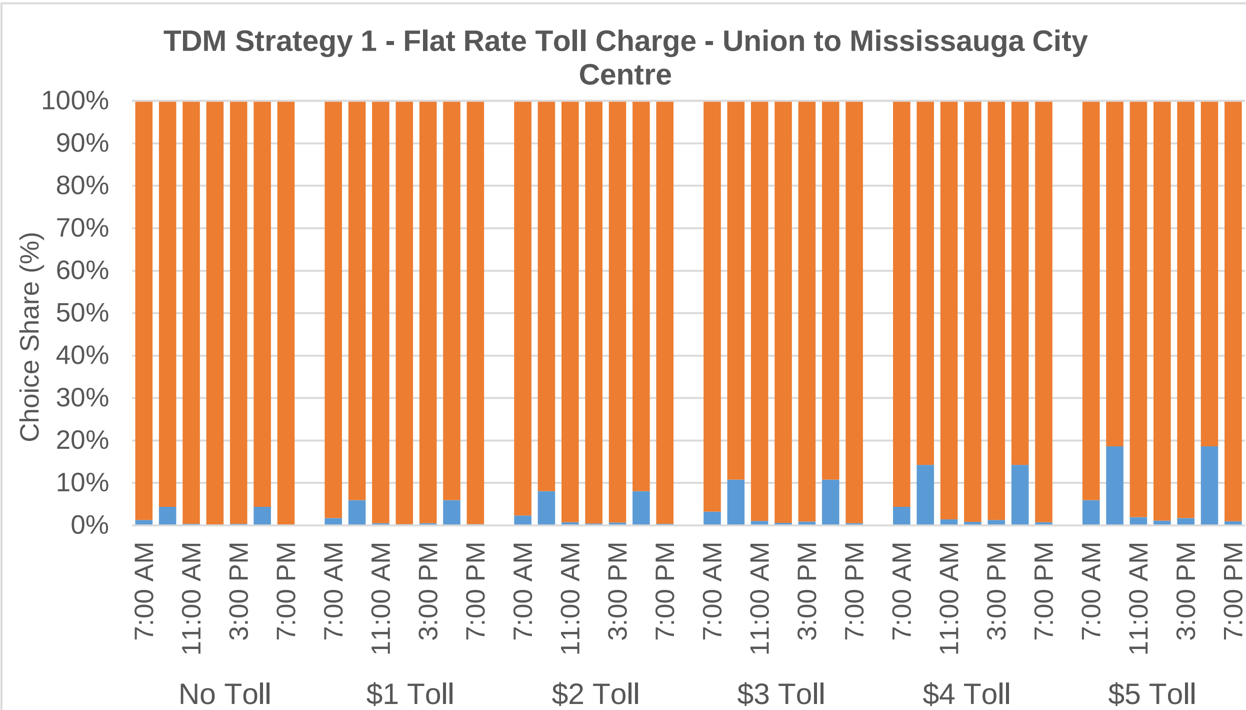


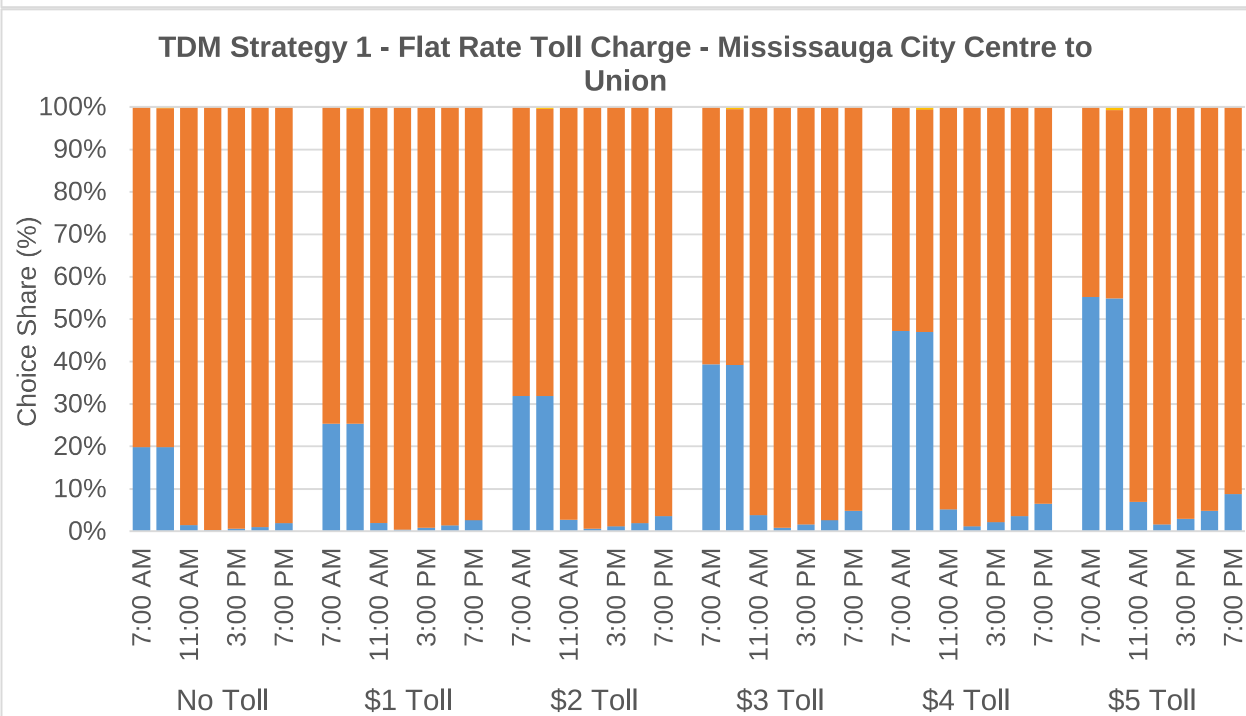


Legend

AUTO - Local no Highway | AUTO - Highway no Toll | AUTO - Highway w Toll
TRANSIT - Local | TRANSIT - Regional | t-q | t+q

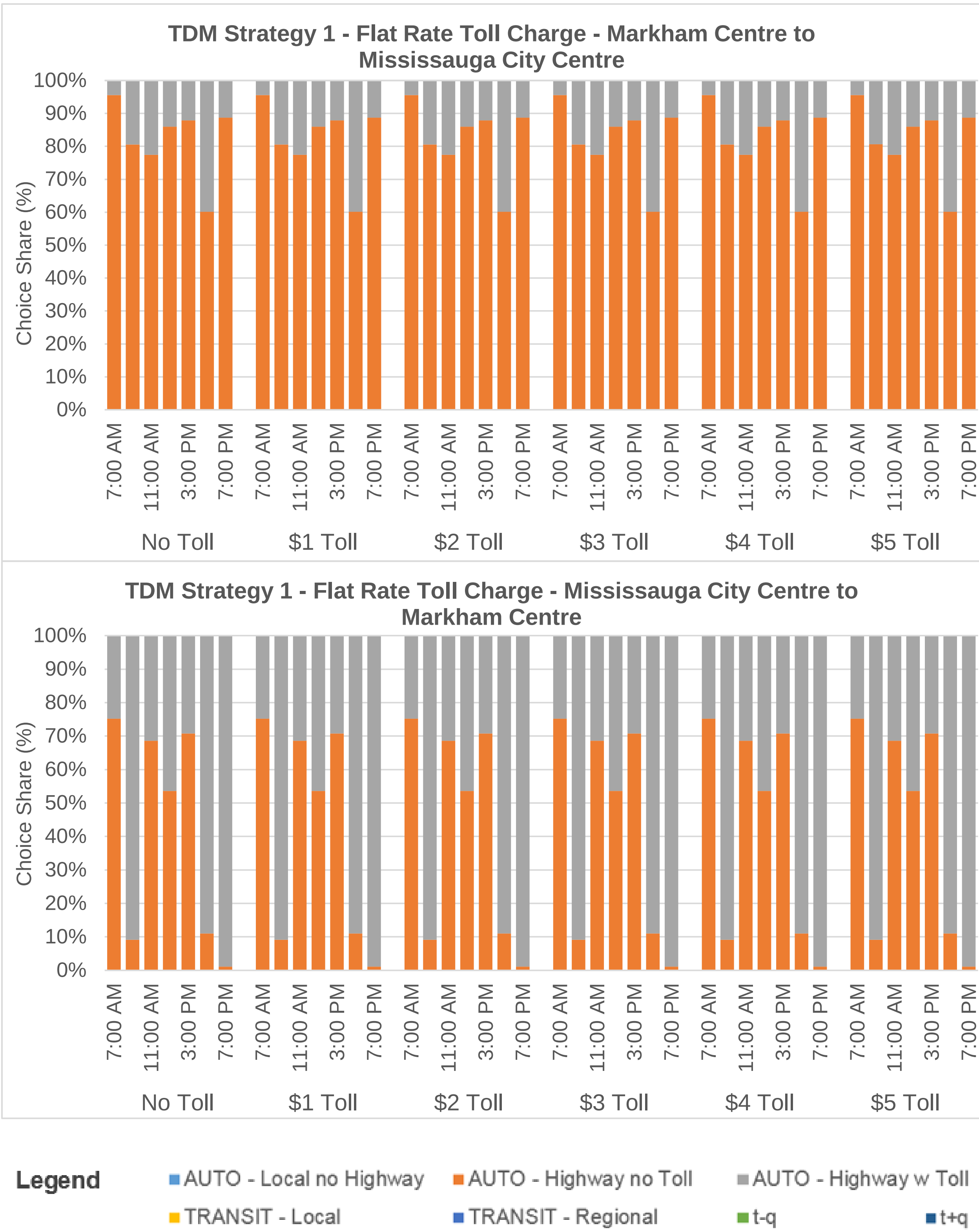
Union & Mississauga City Centre Corridor



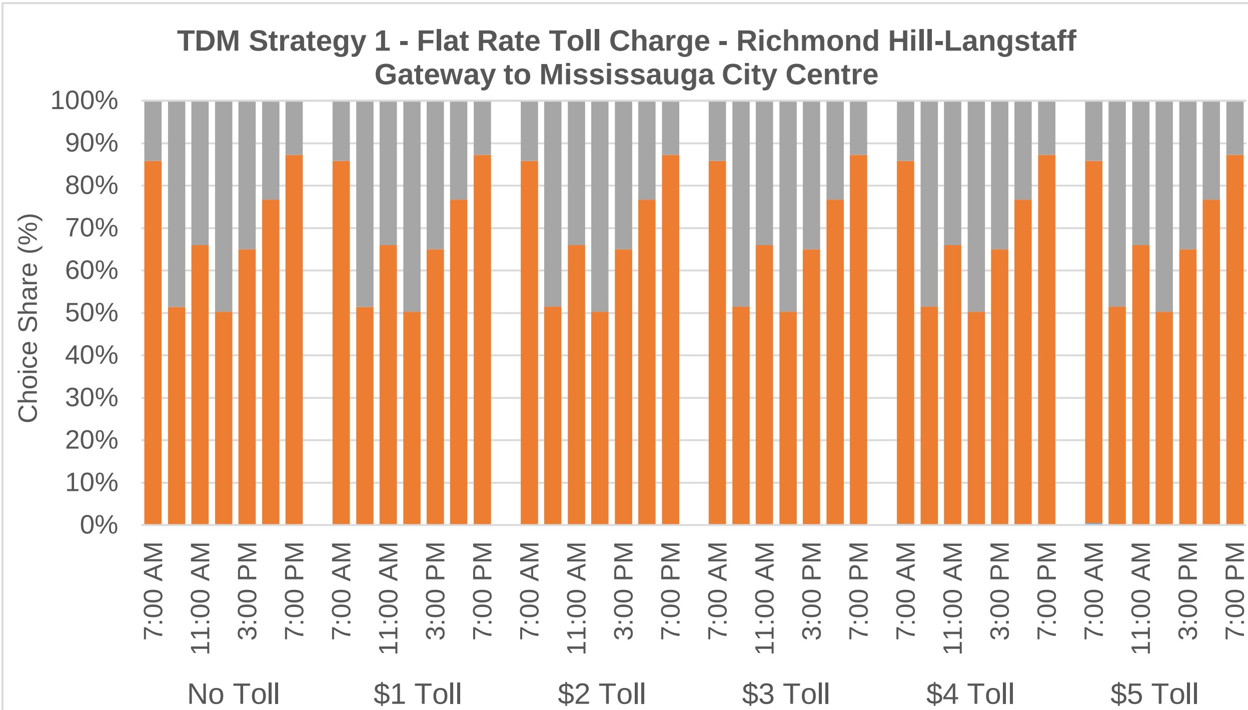


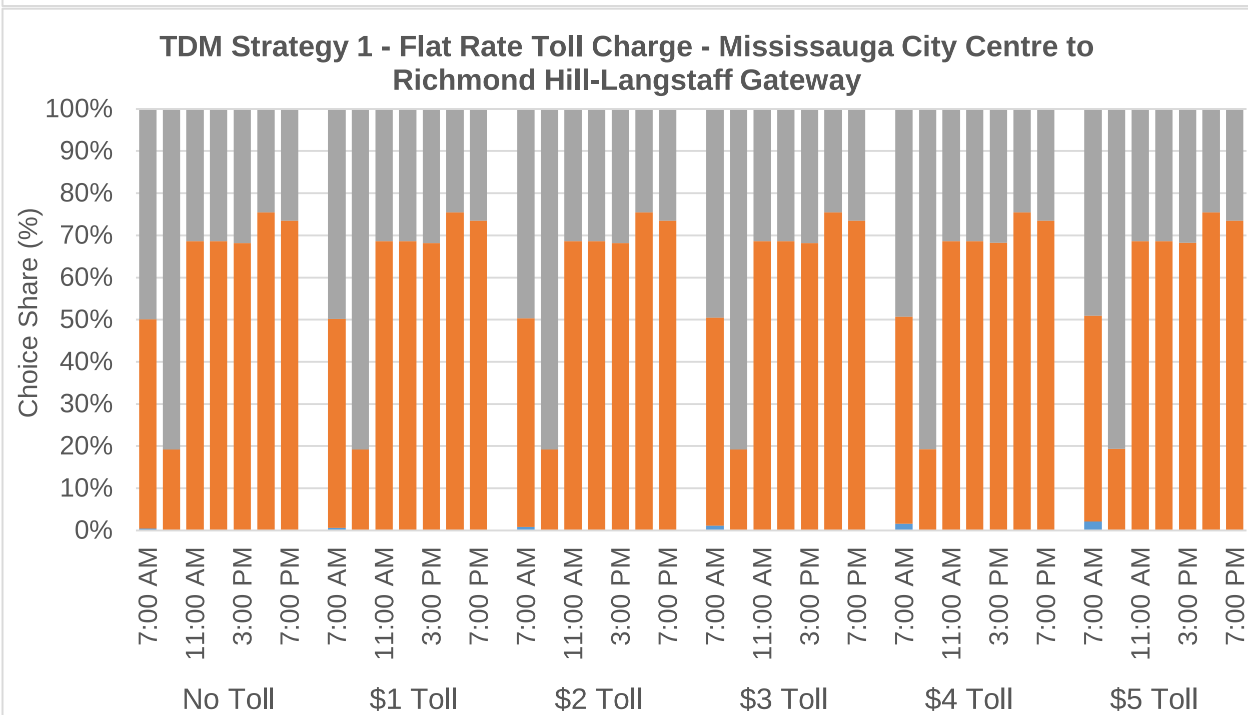
Legend AUTO - Local no Highway | AUTO - Highway no Toll | AUTO - Highway w Toll | TRANSIT - Local | TRANSIT - Regional | t-q | t+q

Markham Centre & Mississauga City Centre Corridor

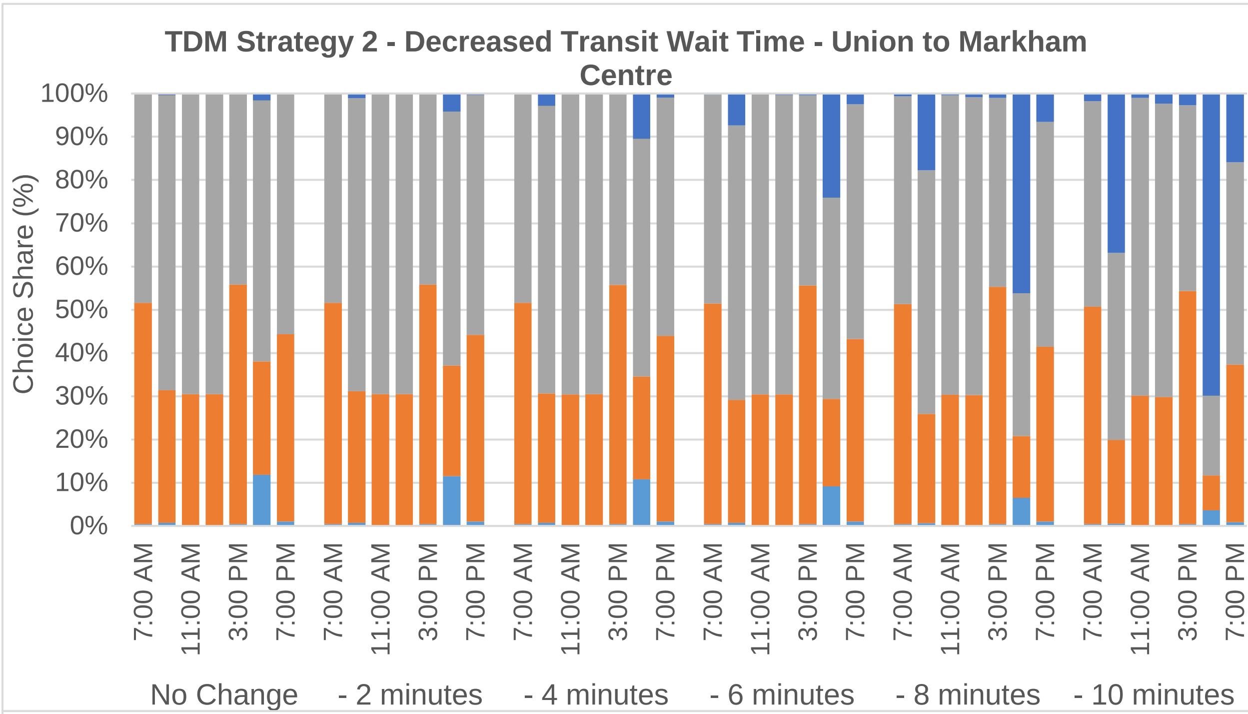


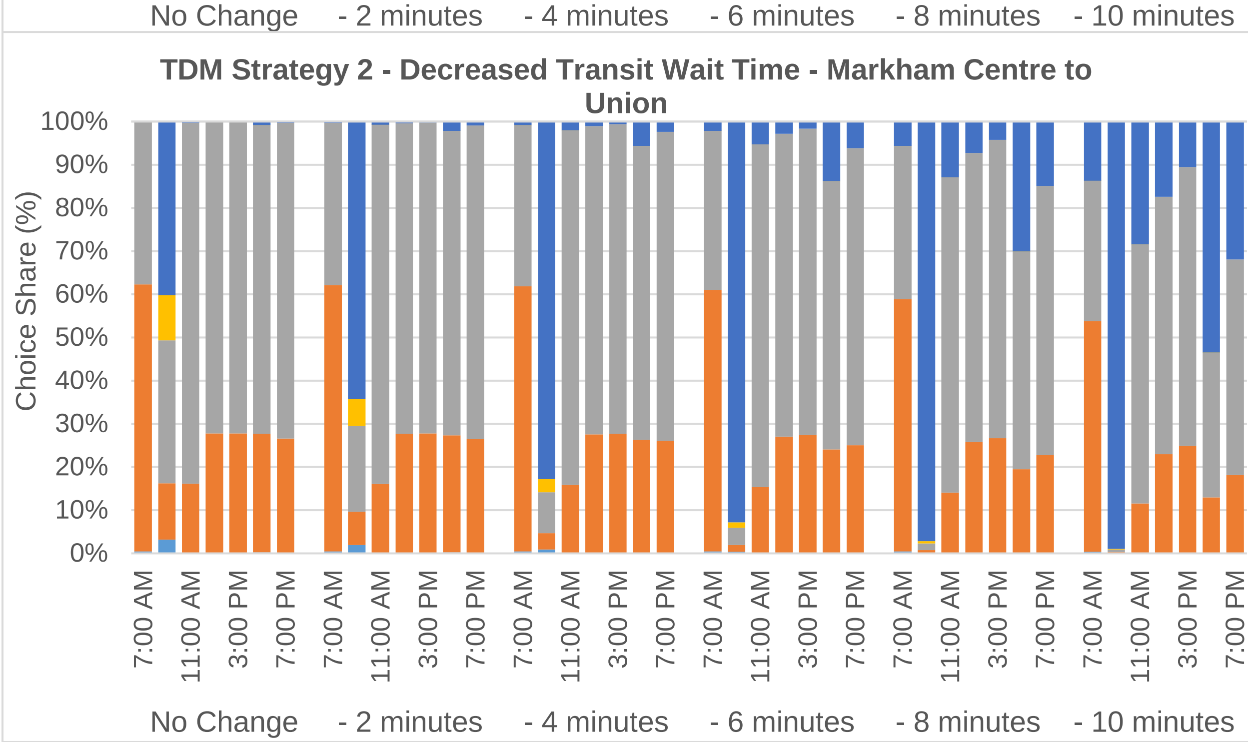
Richmond Hill-Langstaff Gateway & Mississauga City Centre



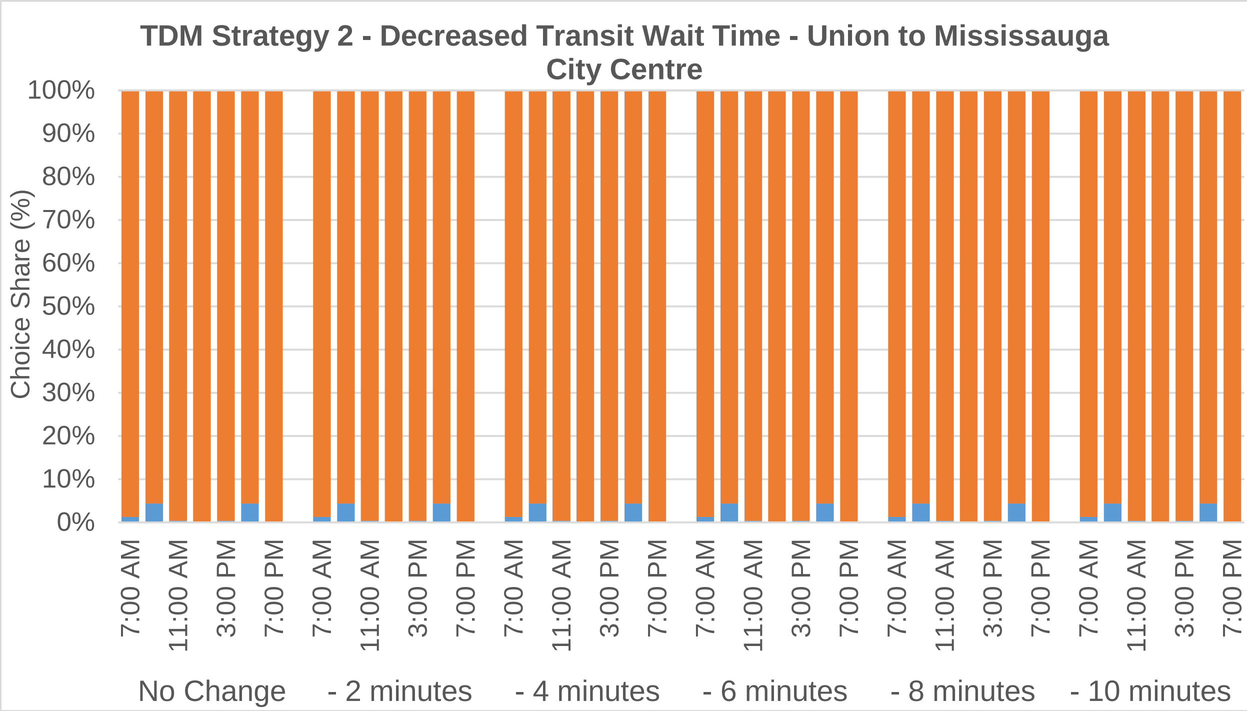


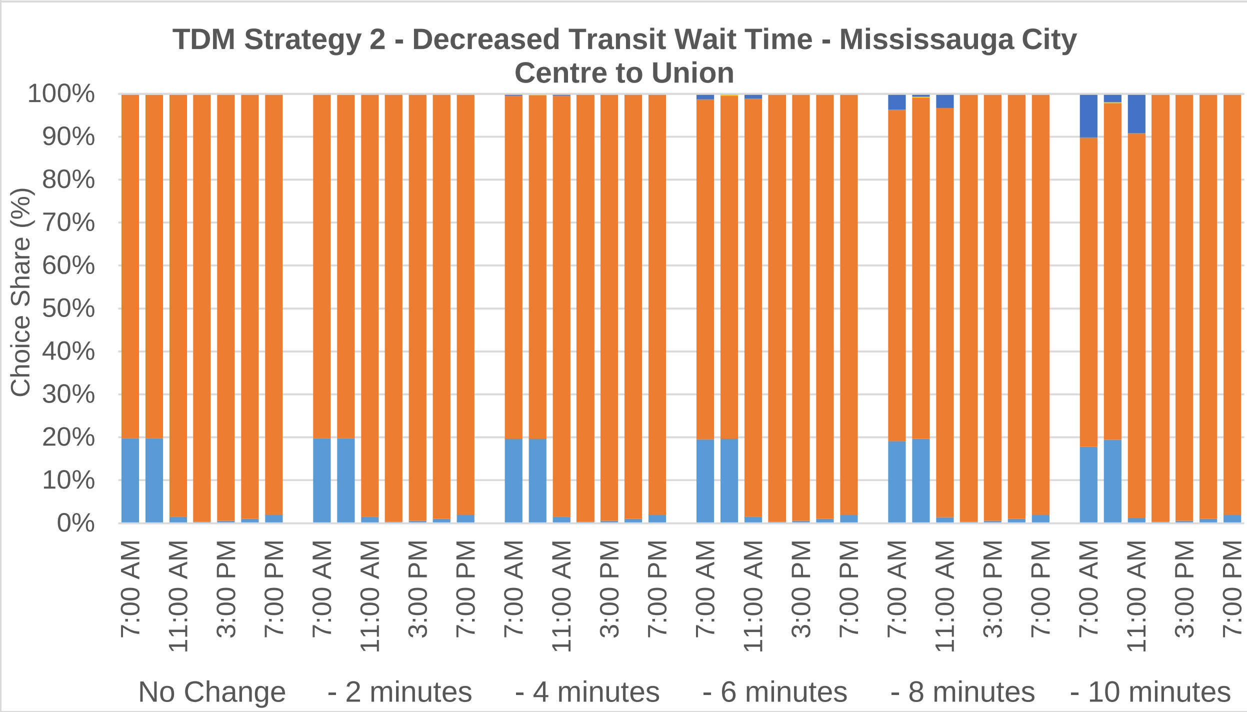
Union & Markham Centre Corridor





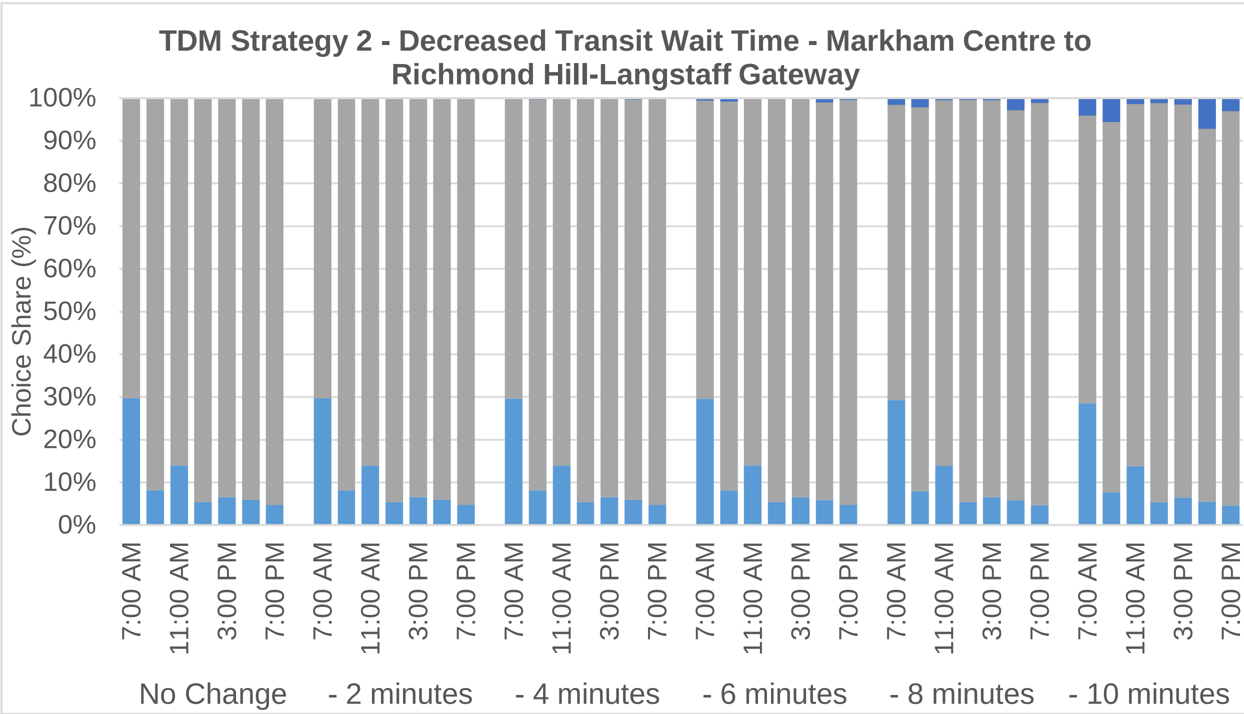
Union & Mississauga Corridor

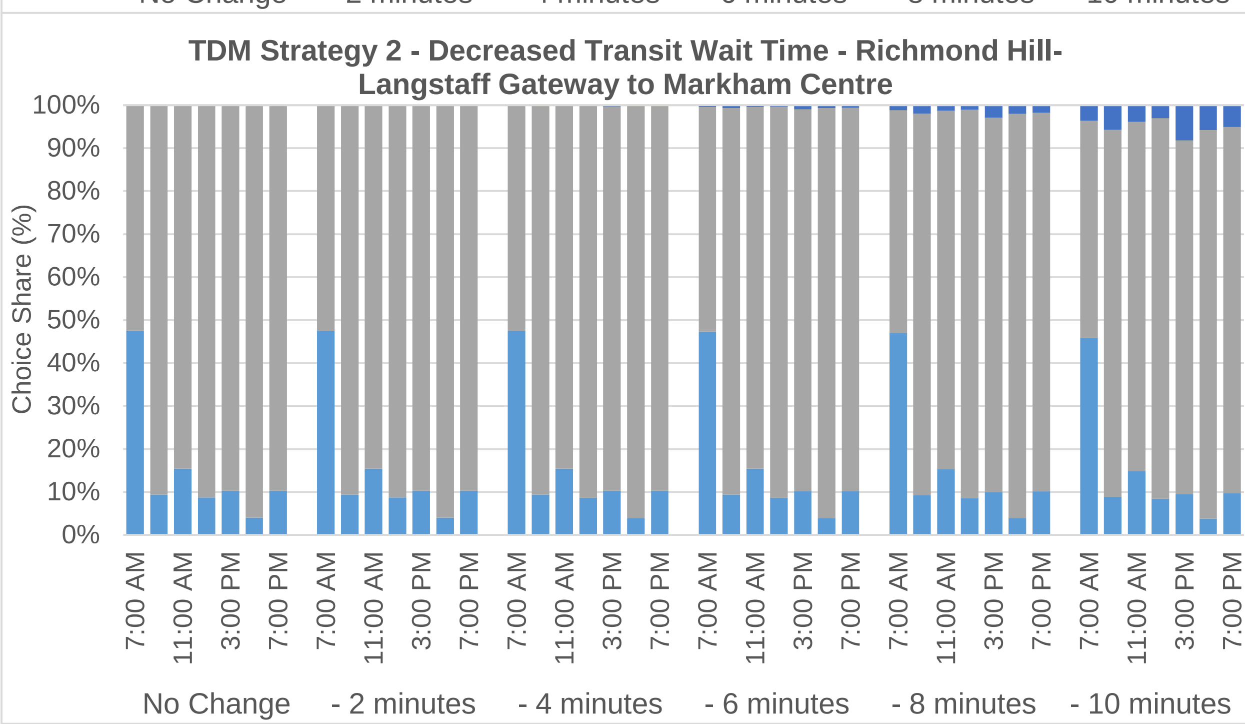




Legend
AUTO - Local no Highway
AUTO - Highway no Toll
AUTO - Highway w Toll
TRANSIT - Local
TRANSIT - Regional
t-q
t+q

Markham Centre & Richmond Hill-Langstaff Gateway Corridor



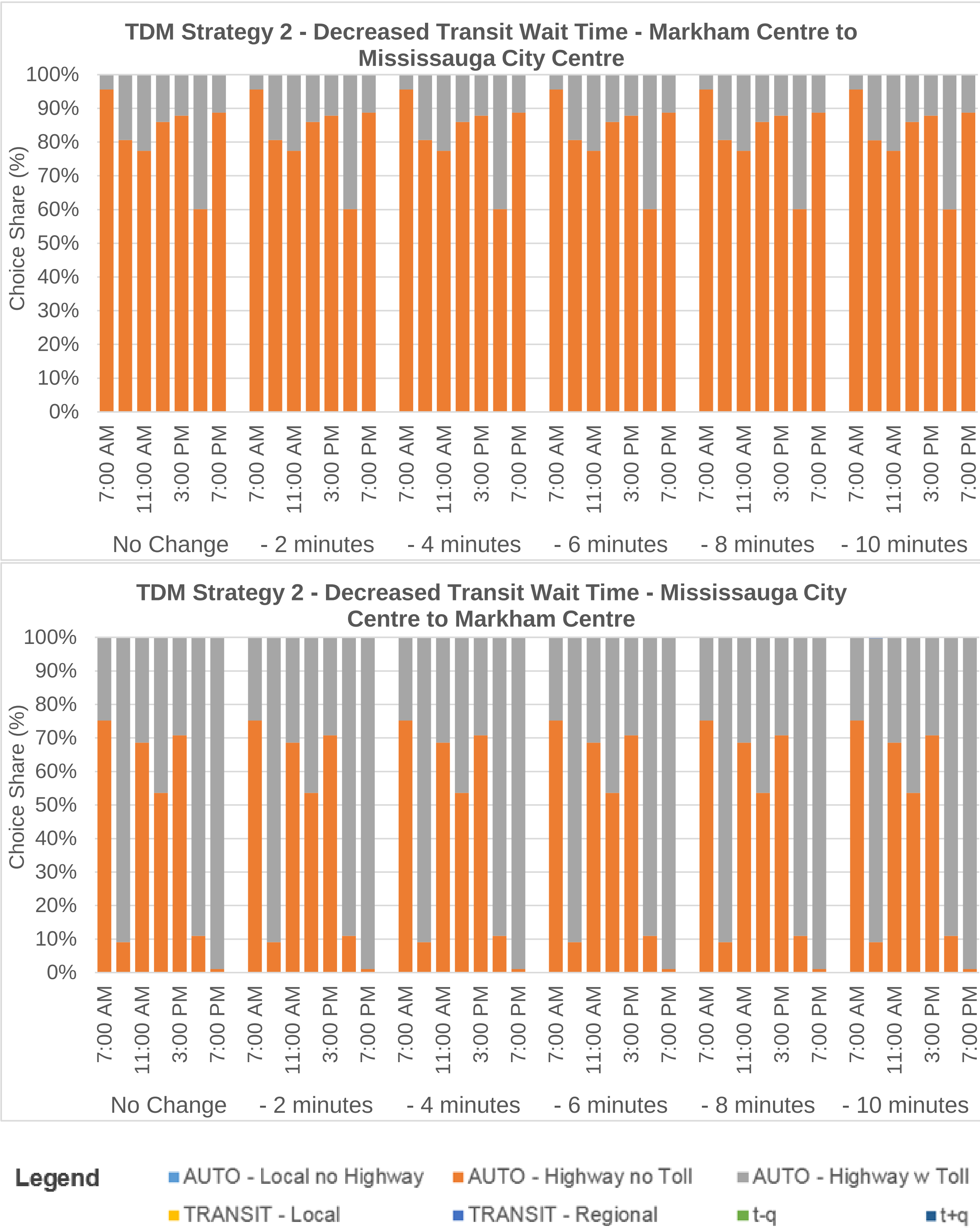


Legend

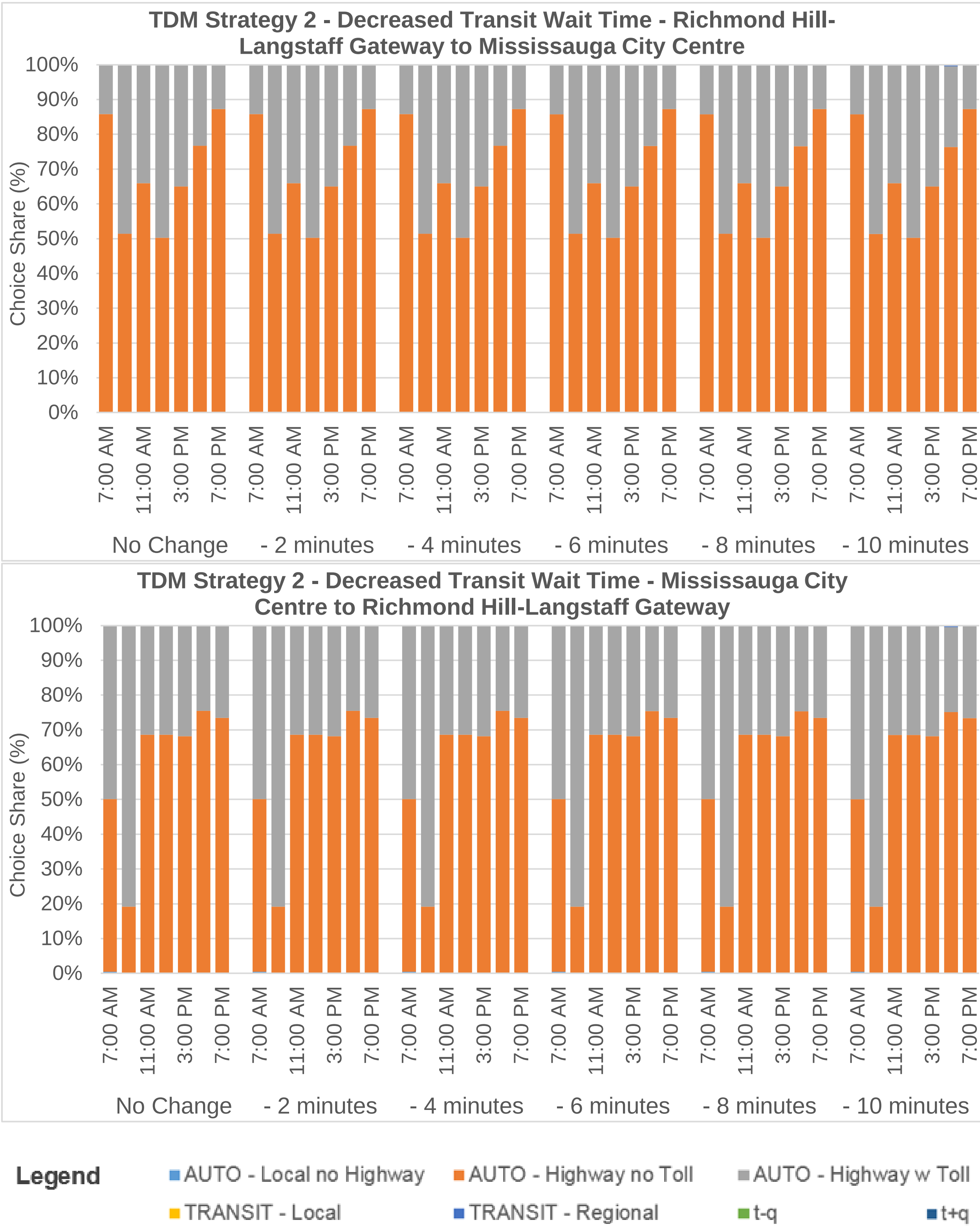
AUTO - Local no Highway | AUTO - Highway no Toll | AUTO - Highway w Toll

TRANSIT - Local | TRANSIT - Regional | t-q | t+q

Markham Centre & Mississauga City Centre Corridor

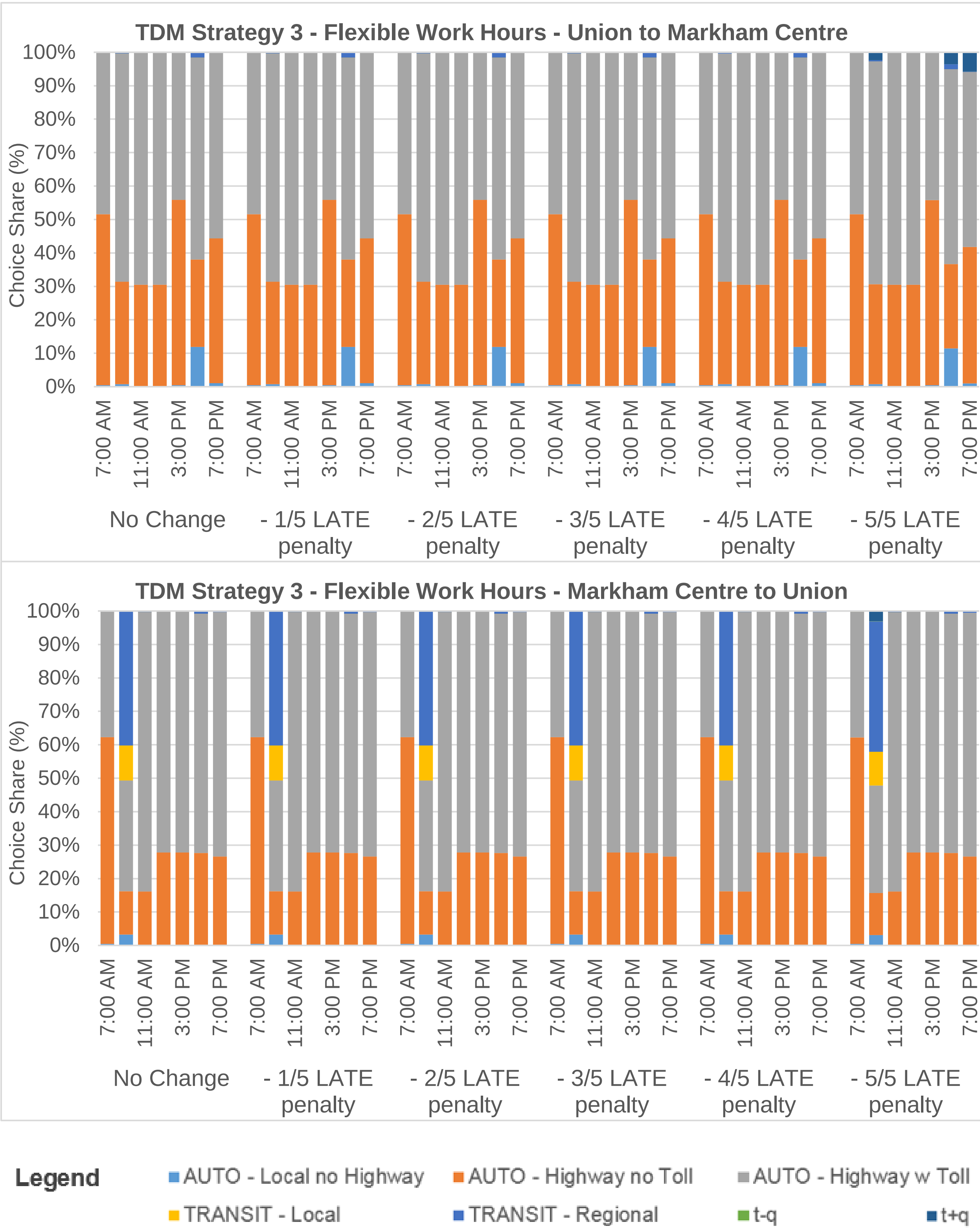


Richmond Hill-Langstaff Gateway & Mississauga City Centre Corridor

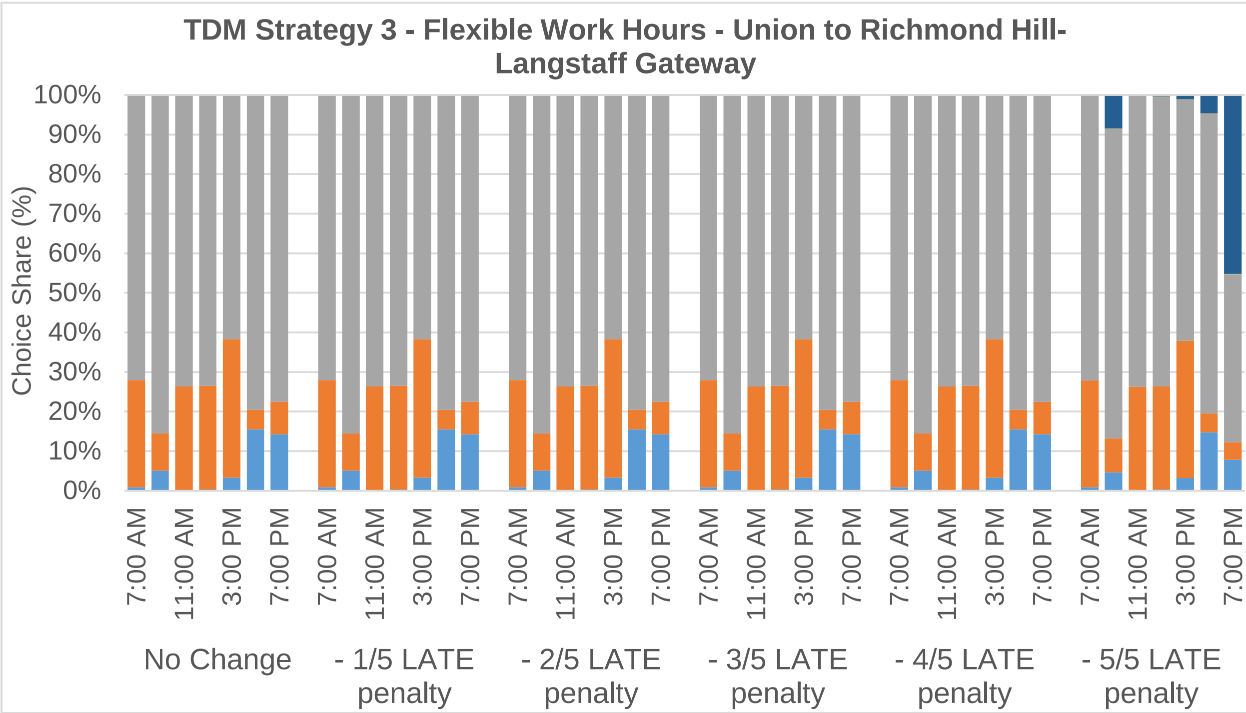


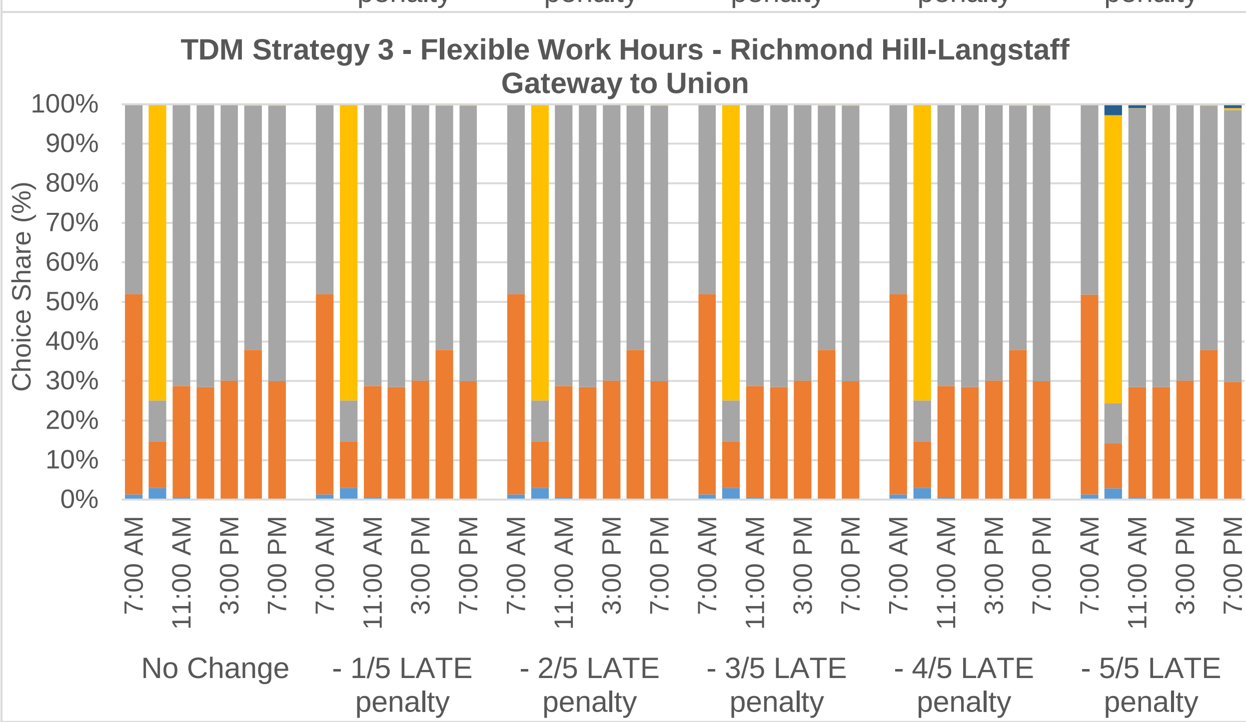
C.3 TDM STRATEGY 3 – FLEXIBLE WORK HOURS

Union & Markham Centre Corridor



Union & Richmond Hill-Langstaff Gateway Corridor

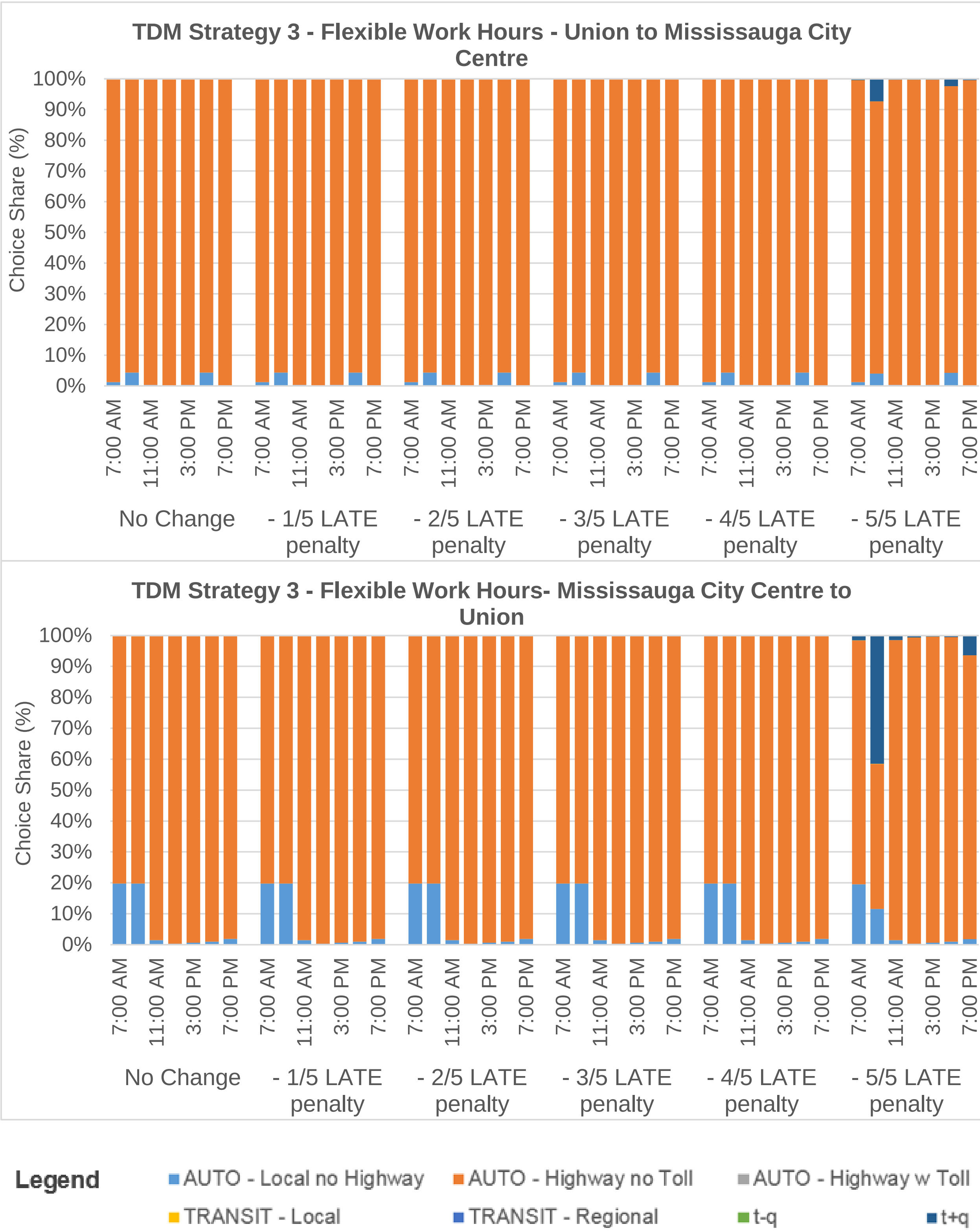




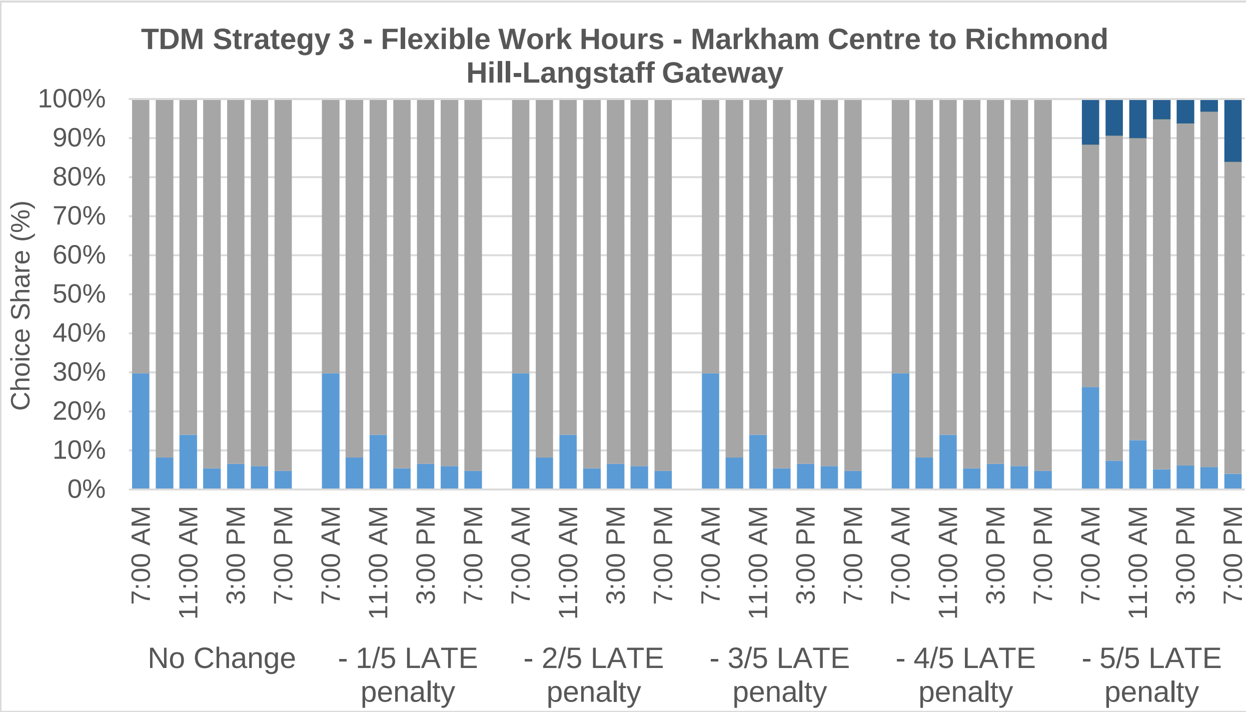
Legend

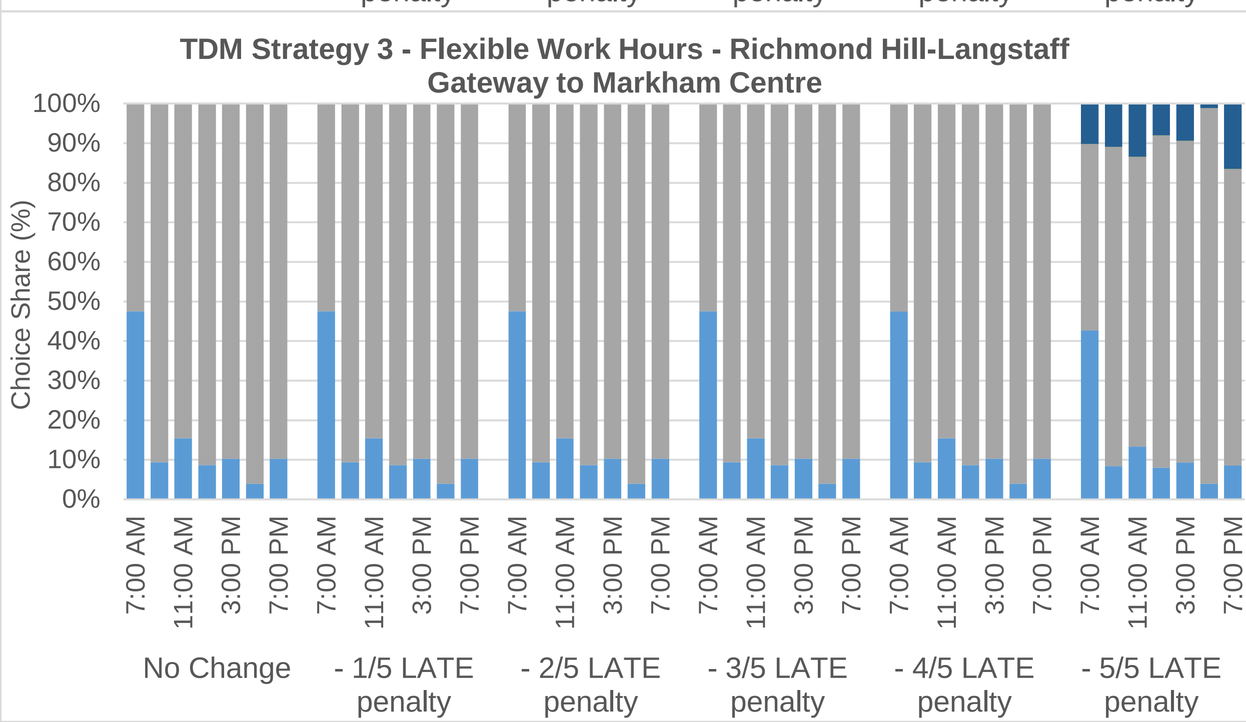
AUTO - Local no Highway | AUTO - Highway no Toll | AUTO - Highway w Toll
TRANSIT - Local | TRANSIT - Regional | t-q | t+q

Union & Mississauga City Centre Corridor



Markham Centre & Richmond Hill-Langstaff Gateway Corridor

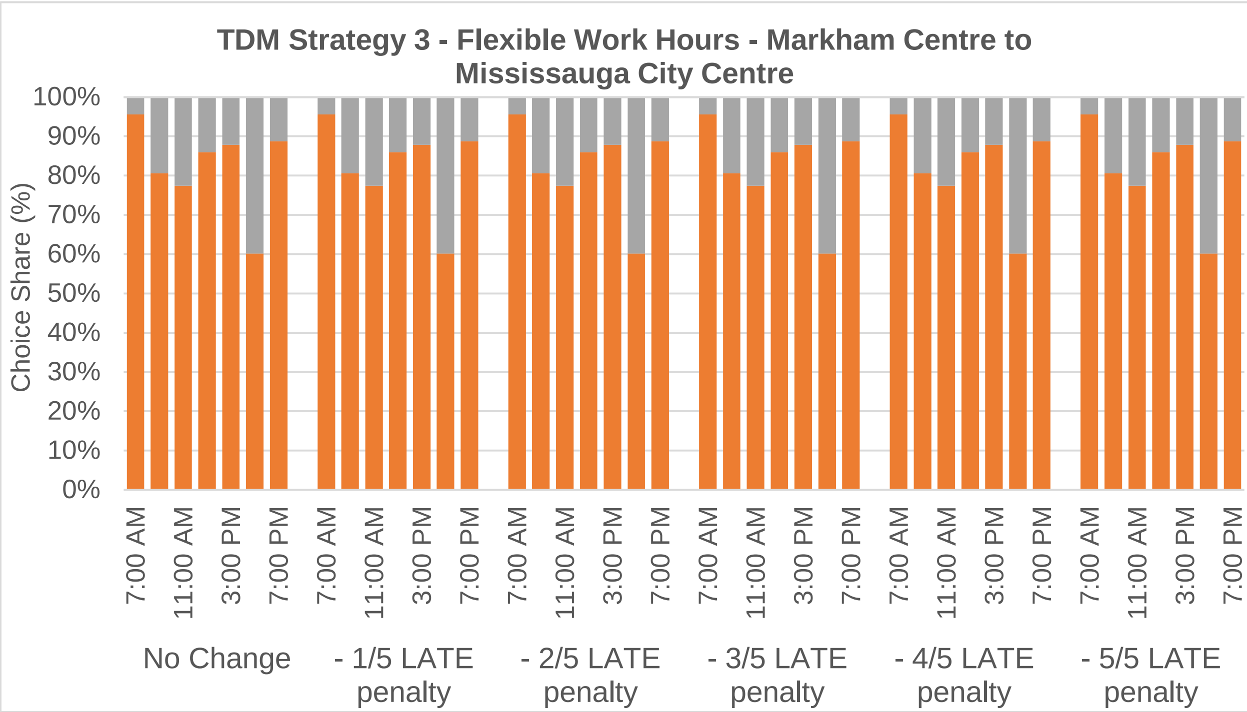


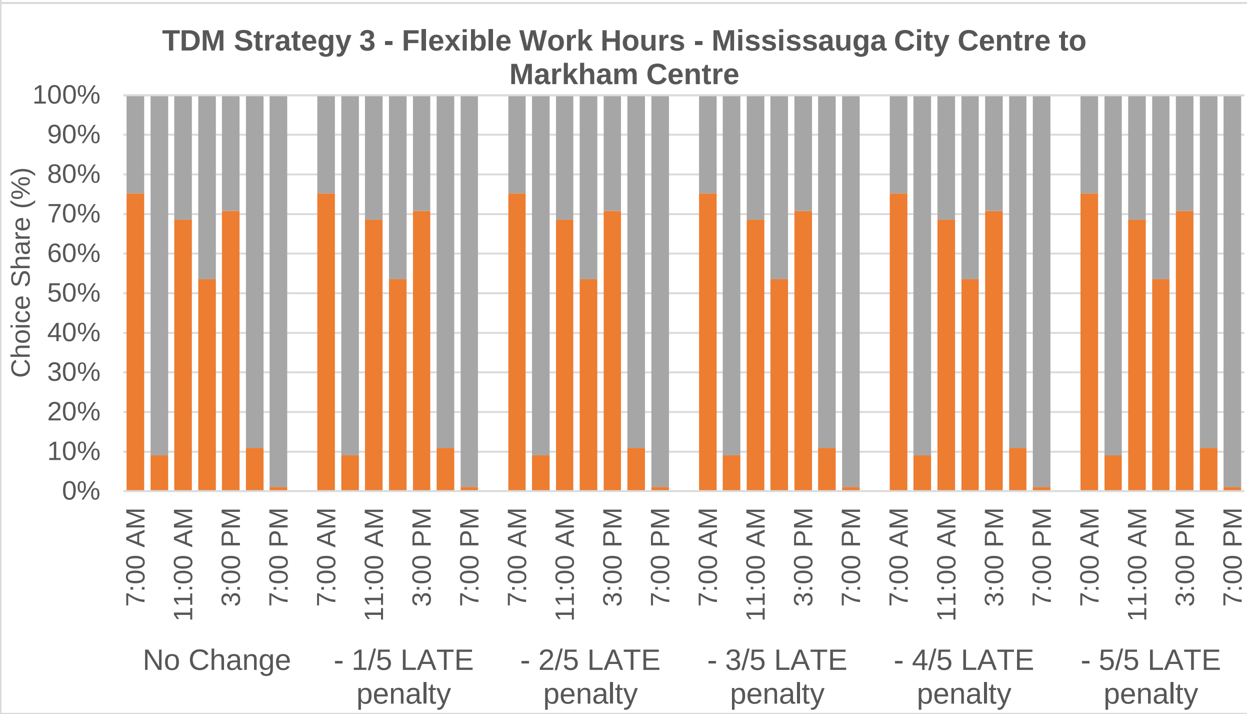


Legend

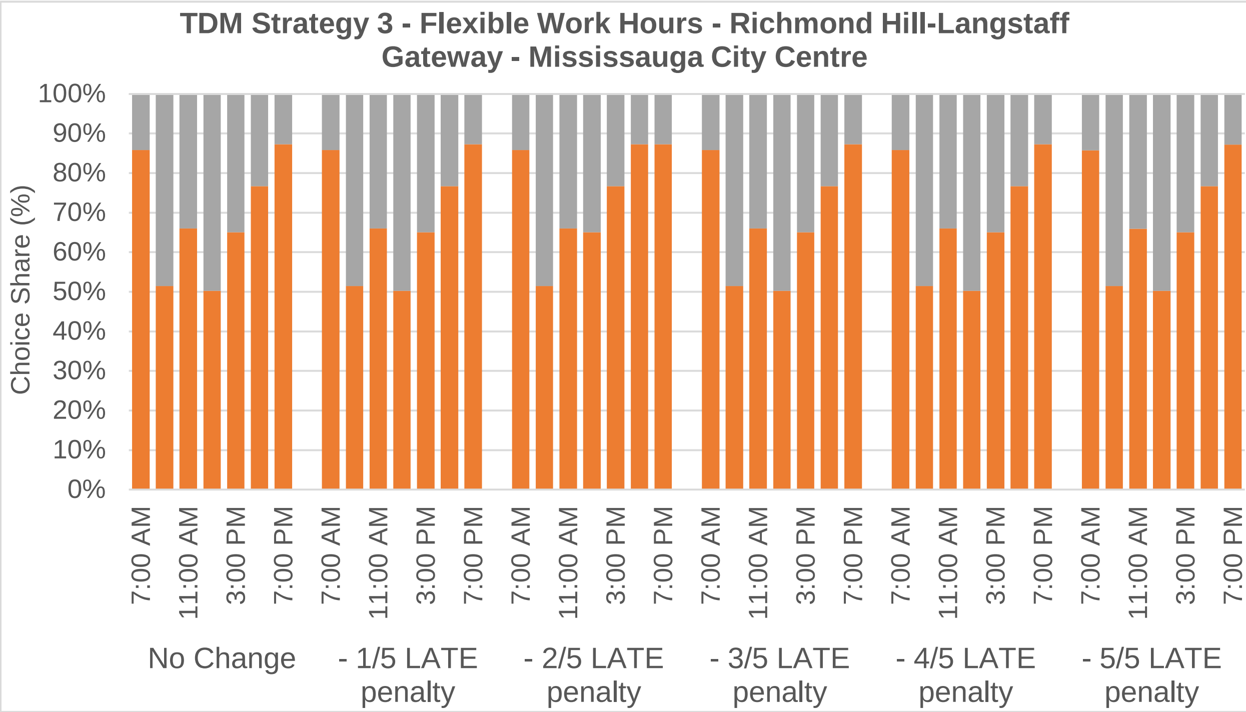
AUTO - Local no Highway
AUTO - Highway no Toll
AUTO - Highway w Toll
TRANSIT - Local
TRANSIT - Regional
t-q
t+q

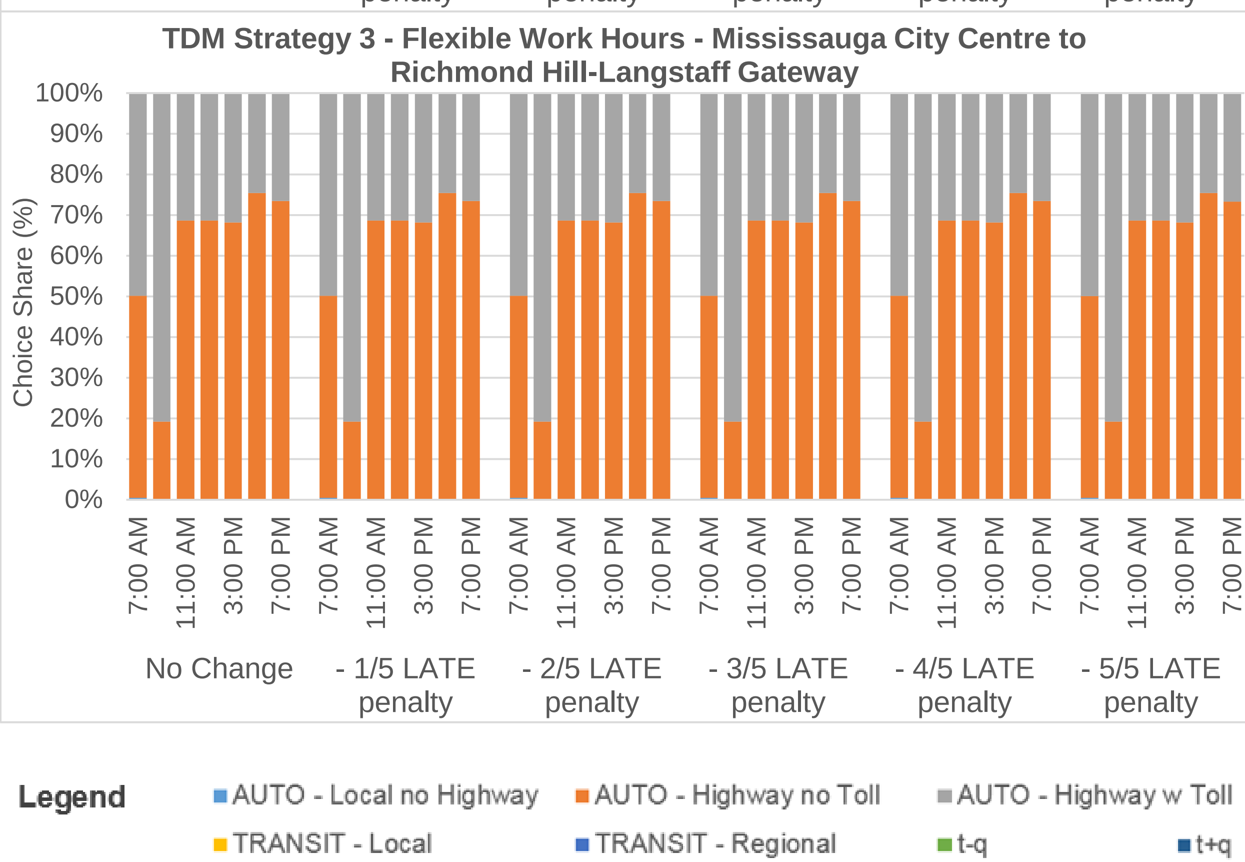
Markham Centre & Mississauga City Centre Corridor



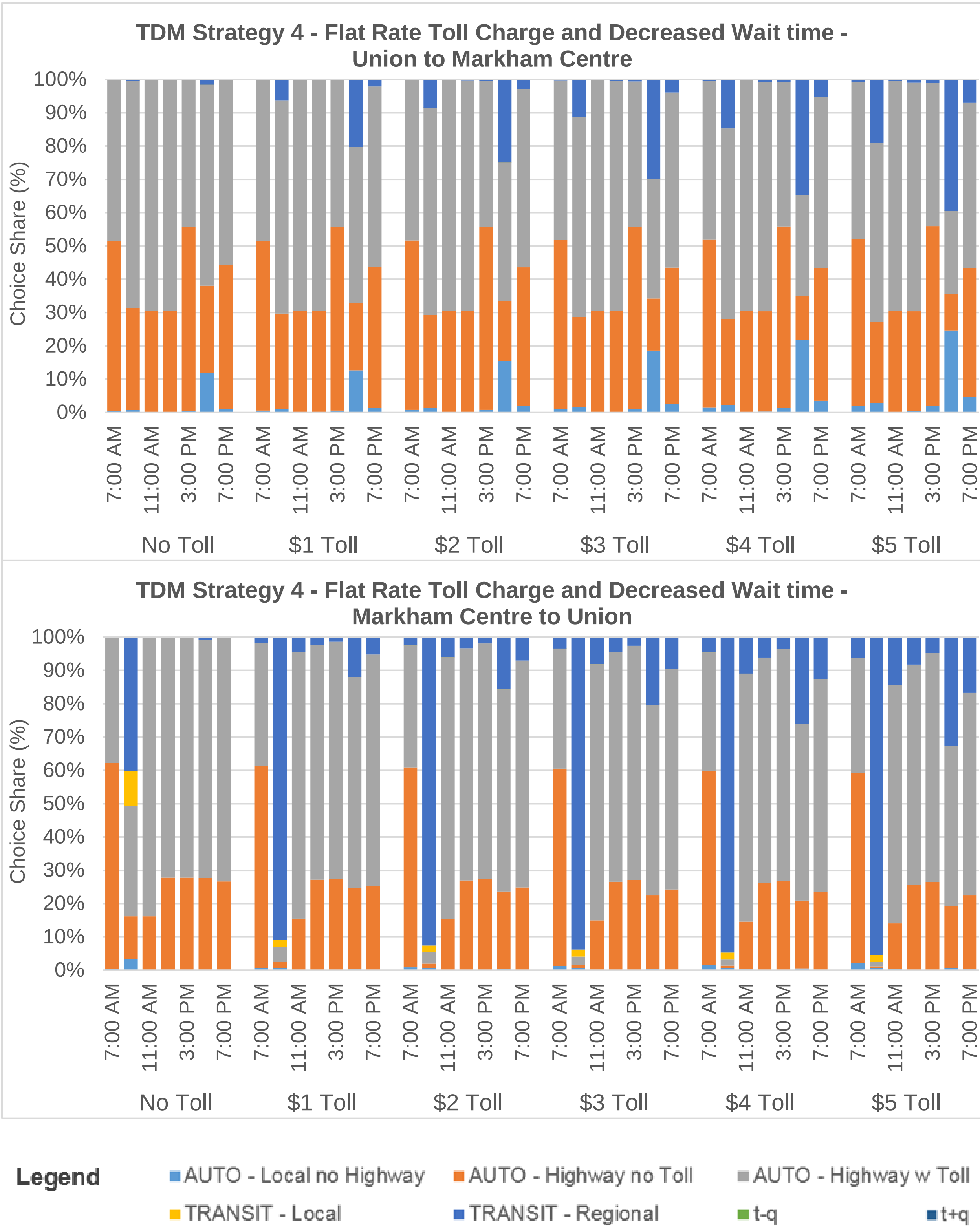


Richmond Hill-Langstaff Gateway & Mississauga City Centre Corridor

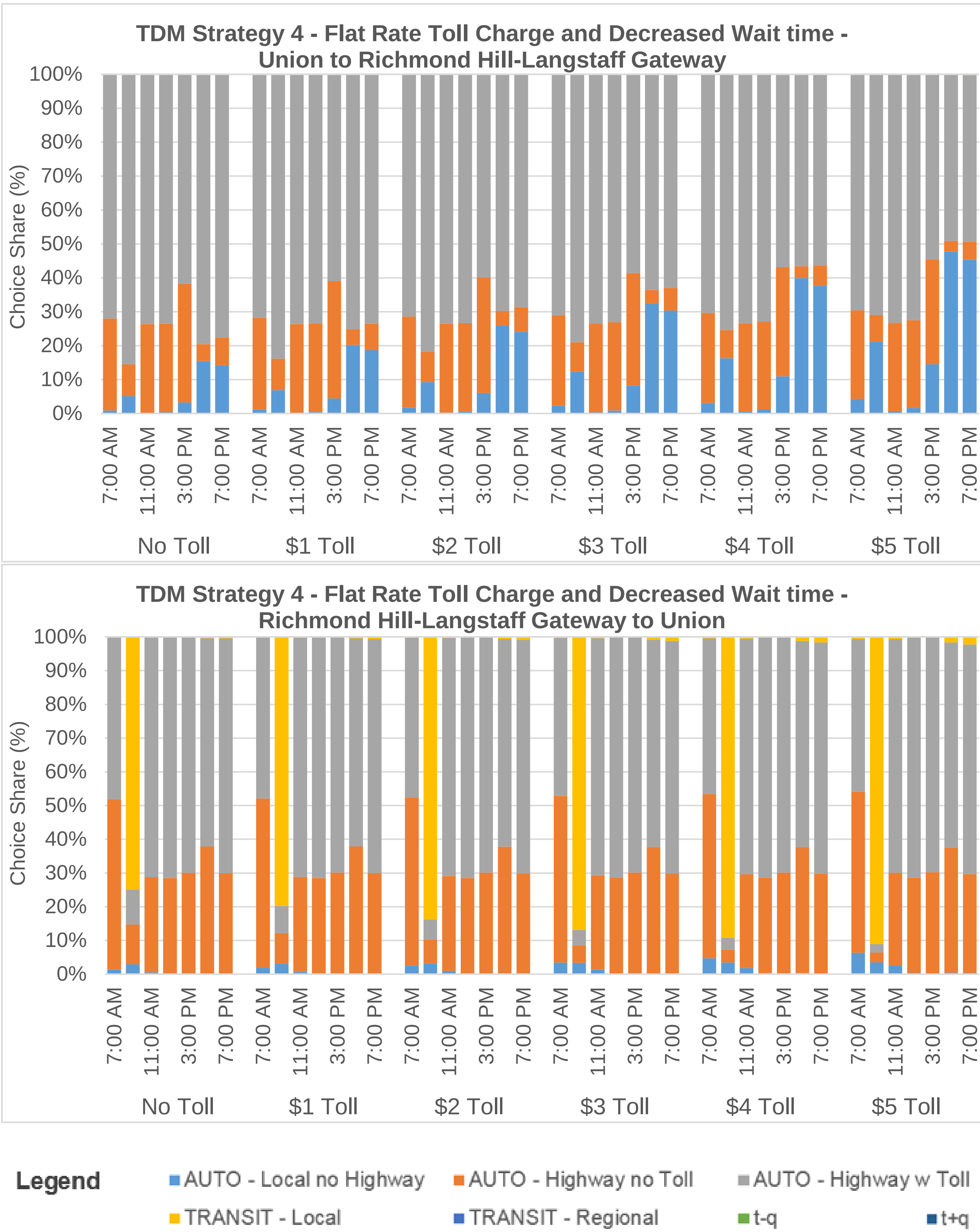




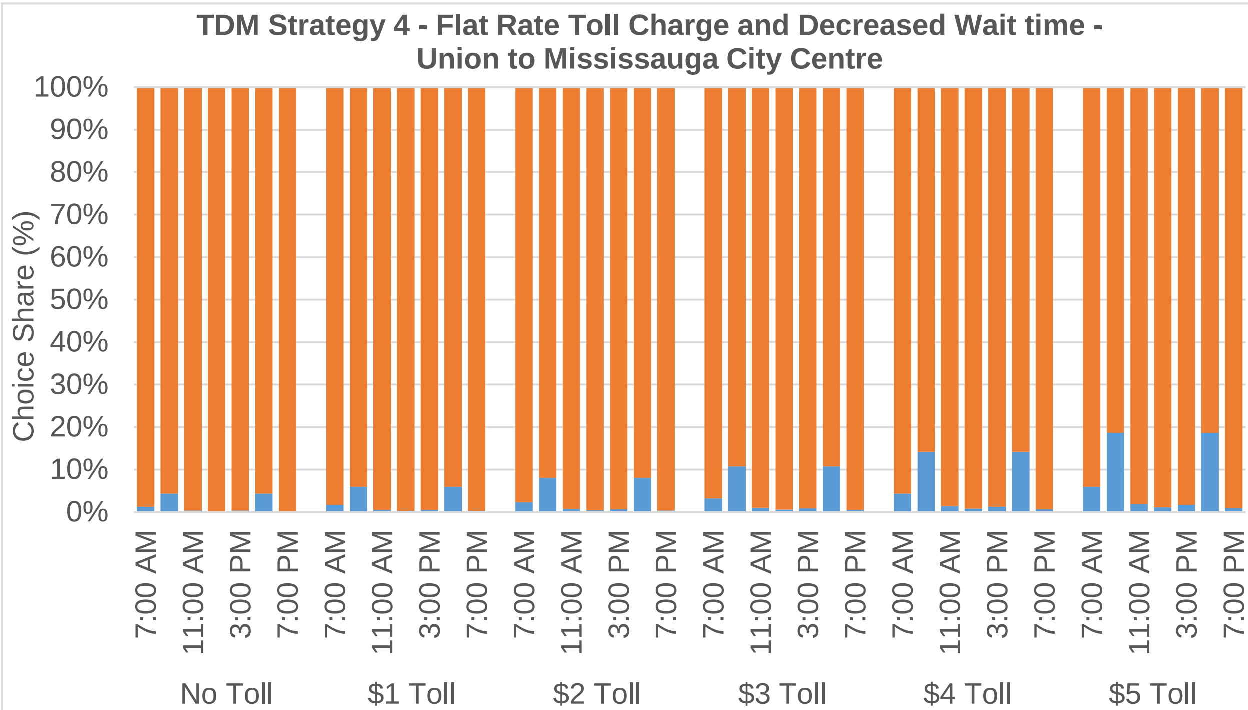
Union & Markham Centre Corridor

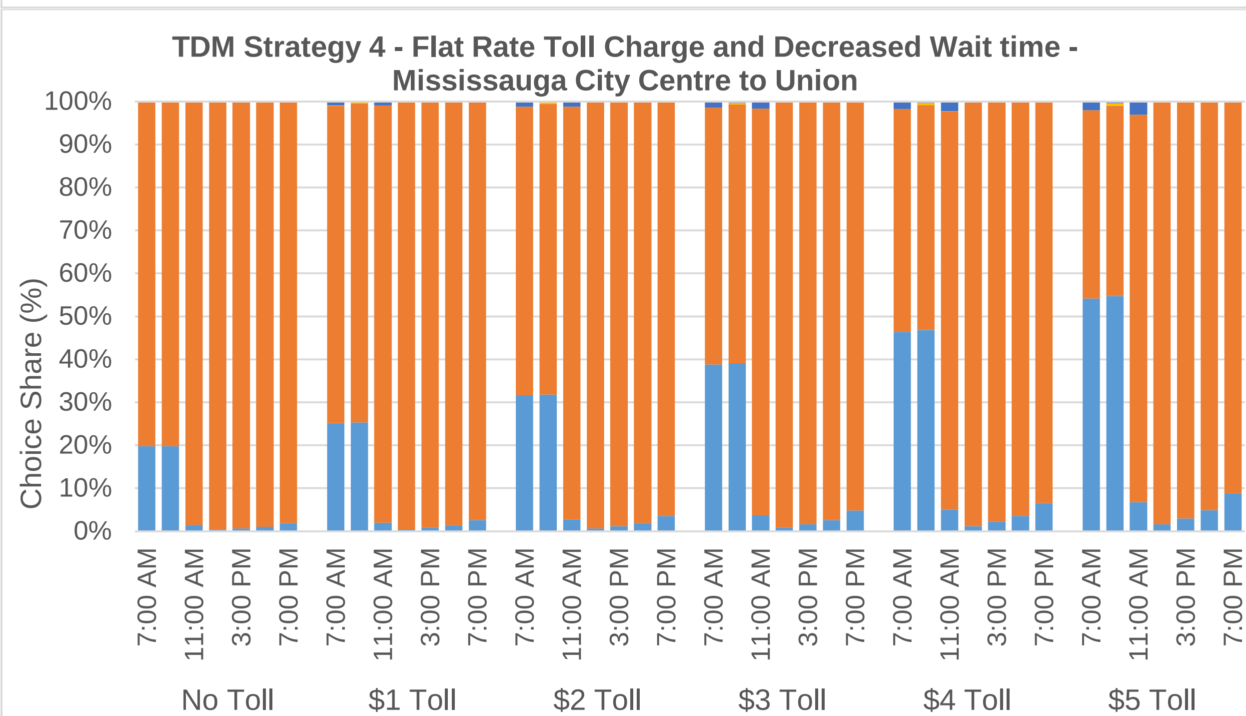


Union & Richmond Hill-Langstaff Gateway Corridor



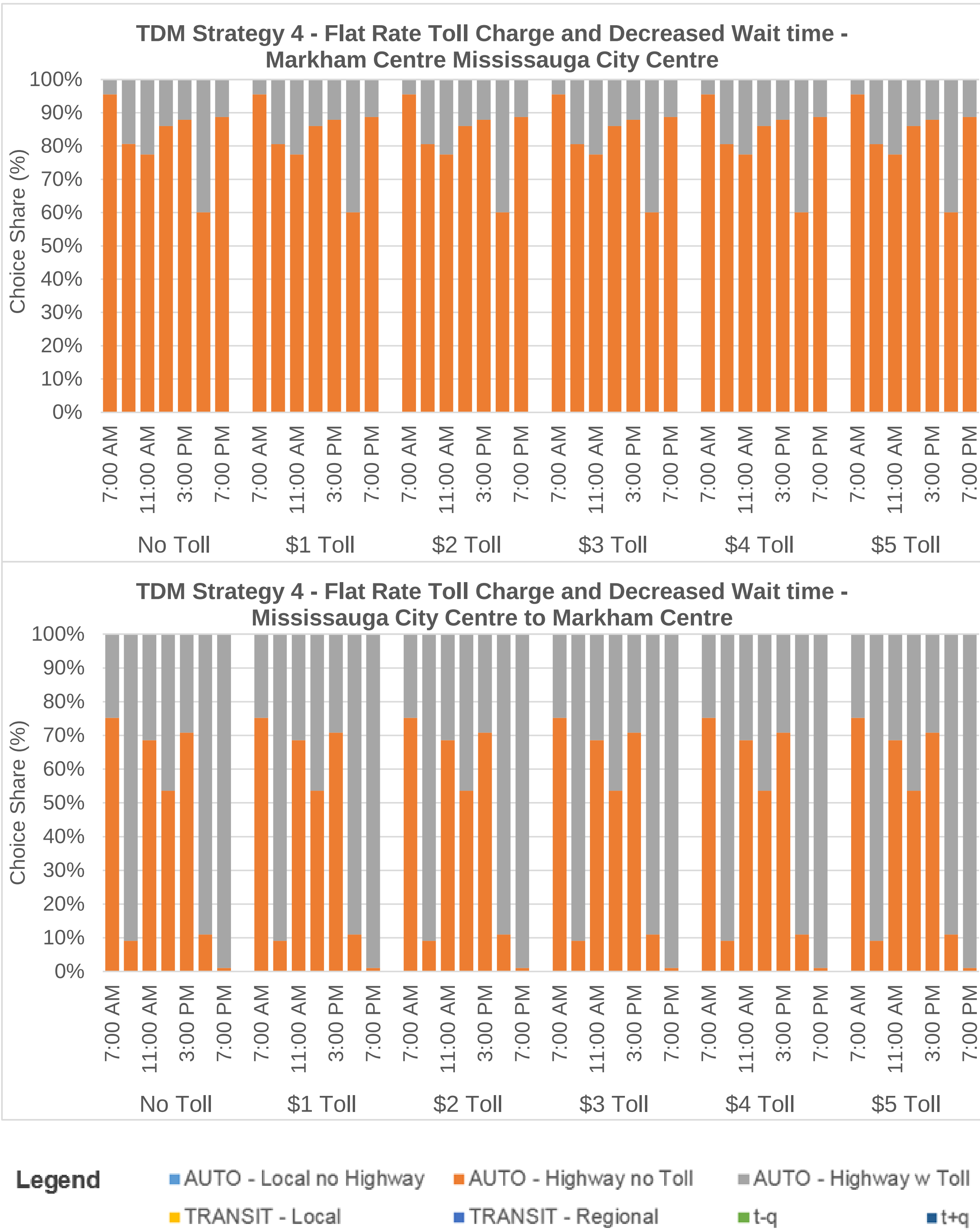
Union & Mississauga City Centre Corridor



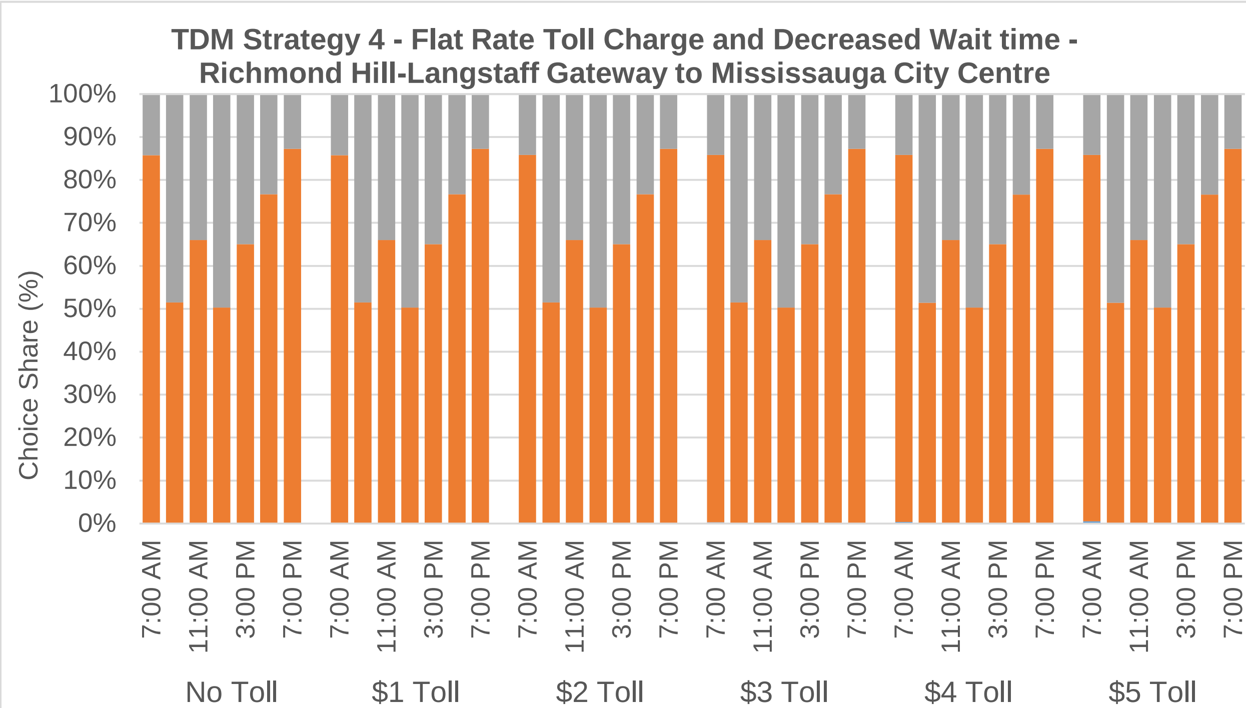


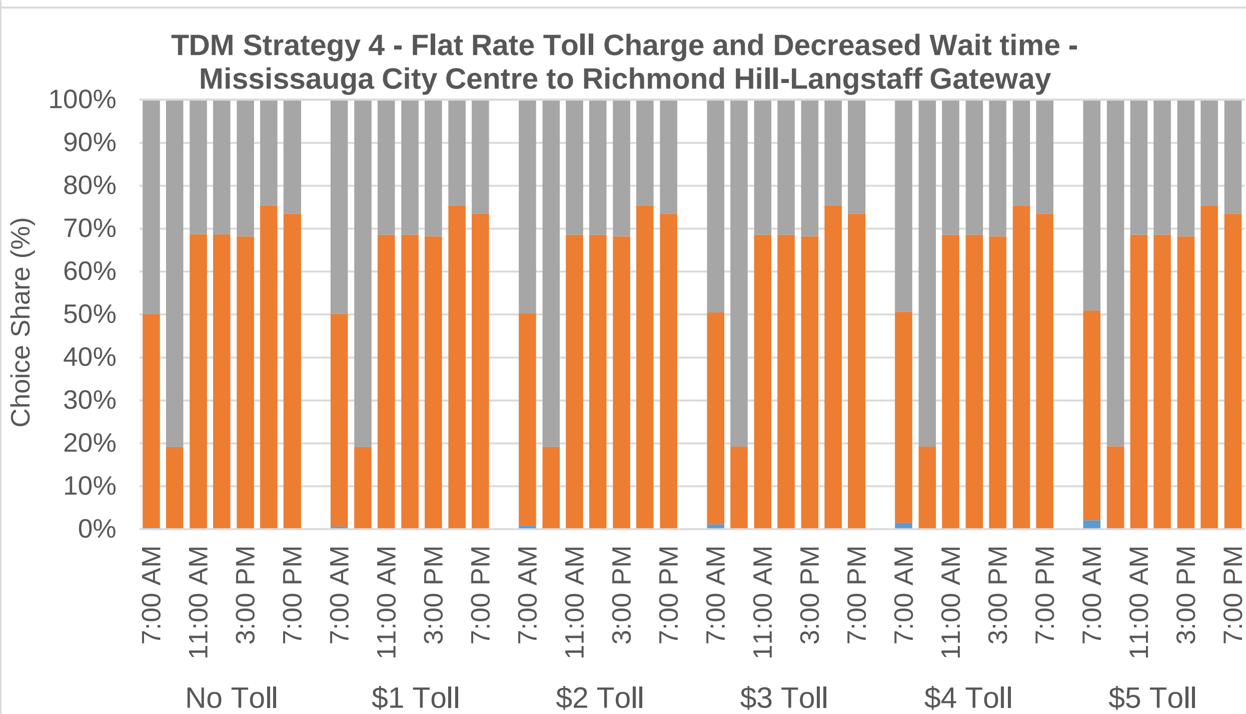
Legend AUTO - Local no Highway | AUTO - Highway no Toll | AUTO - Highway w Toll | TRANSIT - Local | TRANSIT - Regional | t-q | t+q

Markham Centre & Mississauga City Centre Corridor



Richmond Hill-Langstaff Gateway & Mississauga City Centre Corridor





Legend

AUTO - Local no Highway | AUTO - Highway no Toll | AUTO - Highway w Toll

TRANSIT - Local | TRANSIT - Regional | t-q | t+q

APPENDIX D – CALIBRATION PROCEDURES

One of the major limitations of the model presented in this thesis is the level of inaccuracy associated with the uncalibrated model. Due to the way in which the alternatives within the choice set have been specified, it was not possible to calibrate the model to empirical data at the time of development. However, with the emergence of new data sources or a re-specification of the choice set, calibration may be possible in future applications. This appendix presents one possible approach to calibrating the model using the Berkson-Theils method.

Model calibration is required to estimate parameters such as the β coefficients described in Table 20 and employed in equations 2 and 3. As discussed in section A.10 of Appendix A, β coefficients represent the relative weighting of how different generalized cost variables are valued by travellers. The β coefficient values used in this thesis were sourced from existing applications of similar models. Calibration of the model to empirical data would produce β coefficients that more closely reflect the behaviours and attitudes of the specific context under analysis.

A typical model calibration process consists of four steps: data collection and preparation, parameter estimation, evaluation of the statistical significance of parameters, and model validation (Khasnabis & Cynecki, 1988). Data used in calibration includes trip data that reveal the actual choices made, along with information relating to the conditions of the trip, and the travellers making the decisions, such as socio-economic data. Different techniques have been employed in parameter estimation, including Maximum Likelihood Estimate (MLE) and Ordinary Least Squares (OLS) (Train, 2009). In the case of the Berkson-Theil method, the OLS approach is used.

The Berkson-Theil method is a technique used to transform the logit model into a linear form for application of OLS regression. The method was first put forward by Berkson in 1953 for binary logit models, and extended by Theil in 1970 for multinomial logit models (Carrier & Weatherford, 2014; Gottman & Roy, 2008; Theil, 1969). As shown below, the ratio of probabilities between any two given alternatives in a multinomial logit model does not rely on the values of any other alternative (Theil, 1969).

$$P_{ni} = \frac{e^{\beta x_{ni}}}{\sum_j e^{\beta x_{nj}}} \tag{1}$$

$$\frac{P_{ni}}{P_{nk}} = \frac{e^{\beta x_{ni}} / \sum_j e^{\beta x_{nj}}}{e^{\beta x_{nk}} / \sum_j e^{\beta x_{nj}}} = \frac{e^{\beta x_{ni}}}{e^{\beta x_{nk}}} \tag{2}$$

Where :

P_{ni} = probability of alternative i
P_{nk} = probability of alternative k
x_{ni} = utility of alternative i
x_{nj} = utility of alternative j, all possible alternatives
β = coefficient

The natural logarithm of this ratio takes the form of a linear function, y = βx, where y is equal to the ratio of probabilities of the two alternatives under analysis, and x is the difference in utility between the two alternatives. Under this simplified form, the value of β can then be estimated through linear regression.

$$\ln\left(\frac{P_{ni}}{P_{nk}}\right) = \beta'(x_{ni} - x_{nk}) \tag{3}$$

Where :

$\ln\left(\frac{P_{ni}}{P_{nk}}\right)$ = y

$(x_{ni} - x_{nk})$ = x

The estimated β values derived from the linear regression can then be re-inserted into the model in place of any standard values that have been used in lieu of calibrated values. The Berkson-Theils method described is a straightforward method for generating calibrated β values that contribute to a model that more closely represents observed traveller behaviour. Although model calibration is currently limited by the data availability, the method presented could be used in the future when data at the appropriate level of disaggregation becomes available.

Note: This appendix was developed under the guidance and direction of Prof. Chris Bachmann.