Modelling the Impact of Weather Conditions on Active Transportation Travel Behaviour

by

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Abstract

Three weather sensitive multinomial logit models are estimated using the 2001 Transportation Tomorrow Survey in order explore the relationship between weather and home-based work trips within the City of Toronto, focusing on active modes of transportation. The data is restricted to non-captive commuters who have the option of alternating between all five basic modes of auto driver, auto passenger, transit, bike and walk with change in weather. Daily trip rates in various weather conditions are assessed. The combined effect of the daily trip rate and mode choice analysis is applied to several climate change scenarios. A 6^{o}C increase in temperature can increase cycling trips by 17%, and reduce auto-passenger trips by 7%. A 20% increase or decrease in precipitation, however, is found to have much smaller impacts on all modes. Overall, the results confirm that impact of weather on active modes of transportation is significant enough to deserve attention at the research, data collection and planning levels.

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Chapter 1 Introduction and Background

Making non-motorized modes of transportation feasible alternatives for people's daily travel is a part of the solution for some of the major issues our world is facing today, and will be facing in the near future. These issues include oil depletion, climate change, road congestion and increase in health risks such as obesity and heart disease.

If facilitated, promoted, and managed properly active transportation has great potential for being a part of the solution. To illustrate this potential we look at data available for the City of Toronto (Data Management Group 2006) through analysis inspired by Morency et al. (2009). Over 35% of work and school trips made in the City of Toronto are to destinations under 4km. Such short distance trips can be made by either walking or cycling in less than 15 minutes. About 55% of these trips are made by motorized modes such as auto passengers, drivers, transit and school bus and could potentially be made by active modes of transportation. This would result in a mode shift of almost 20% of daily trips in Toronto from motorized to non-motorized modes.

While the potential for active transportation modes in urban areas is relatively well known, some cities have taken advantage of them much better than others. In addition to differences in government policies and practices, factors such as characteristics of the built environment, commuter patterns, demographics and personal preference and attitudes towards different modes of transportation are also influential. Additionally, one of the major contributors to wide utilization of active transportation modes in a city is its climate. This factor is the major motivator of this thesis as it raises questions about the relationship between weather and active transportation travel behaviour.

One of the main questions addressed in this thesis is how mode choice of different demographic groups is affected by elements of weather such as precipitation and temperature. The answer to this question, especially with regards to the bike and walk modes, is anticipated to help develop more successful promotional policies by gearing them towards appropriate audiences. Another question addressed here is whether the impact of weather on walking and cycling flows is large enough to justify the need for a weather "correction" factor for standardizing counts. Additionally the author hopes to contribute to improving travel survey data, and consequently travel demand models, by assessing the limitations of conducting surveys over only a narrow range of weather conditions throughout the year.

Researchers have extensively looked at the impact of transportation activities on the environment for several years; however, the reciprocal relationship, the effect of climate and weather on transportation choices, specifically here the choice to walk or cycle, has remained less explored. While existing research on this topic suggests that this impact is significant there are certain gaps in research that this study aims to fill. Most of the analysis conducted on the topic falls in one of two categories. Some research is conducted at a very aggregate level and does not include detailed enough weather condition and trip specific characteristics (Dill and Carr 2003, Winters et al. 2007, Parkin et al. 2008, Berkim et al. 2006). Others are very location specific, and while they contain very detailed weather data, they fail to capture the influence of socioeconomic characteristics of trip makers and characteristics of other alternative modes (Brandenburg et al. n.a., Thomas et al. 2009, Nankervis 1999, Cools et al. 2010, Bergstrom and Magnusson 2003, Aultman-Hall et al. 2009). There is also very little research done on the relationship between weather and the walk mode compared to the bicycle mode. This thesis aims to close some of these research gaps.

To meet the objectives highlighted above the multinomial logit (MNL) and nested logit modelling approaches are used in investigating the impact of weather on the five basic modes of auto drive, auto passengers, transit, bike and walk. In addition to the basic MNL model, the interaction between weather and age and weather and gender are explored through two sub models. Results of these interaction models help explore the sensitivity of different age and gender groups to various weather conditions in addition to developing better and more accurate models. The focus of this research is to model behaviour of trip makers who are not captive to a limited choice set of alternatives and have the option to switch to other modes of transportation in the case of adverse weather. As a result, the mode choice modeling sample is restricted to individuals who hold a driver's licence and have access to a vehicle within their household. Furthermore, by setting constraints on trip distance and location of origin and destination, trips are limited to only those that could potentially be made using all the five modes under study. Home-based work trips meeting the above criteria are sampled from the 2001 Transportation Tomorrow Survey (TTS). Trips are limited to work purpose trips because the walk and cycle modes are only capture for work and school trips. School trips are not modeled here due to the expected differences in travel behaviour relating to the work and school trip purposes. Travel data are combined with hourly weather data reported by Environment Canada for the City of Toronto. Weather features incorporated in the study include categories of temperature ranges, wind speed and several precipitation conditions.

Further analysis is conducted on the impact of weather conditions on trip generation, in addition to mode choice. Results of this analysis are combined with the results of the mode choice model and applied to several climate change scenarios. This provides a measure of sensitivity of each mode to expected changes in the climate, in addition to short term changes in weather conditions.

Some preliminary analysis is also performed on the relationship between weather and cycling flows using about 9 years of bicycle flow data available for a high bicycle traffic flow location in Toronto.

The remainder of this document is structured as follows. The next chapter provides a summary and highlights the gaps in the current state of research on the topic of the impact of weather conditions on active transportation behaviour. The various sources and the characteristics of the data used for the analysis conducted for this research are then introduced. This is followed by a discussion of some preliminary analysis of the available bicycle flow data. Next, the multinomial logit modelling theory, specifications and results of the modelling work are presented and discussed. After this discussion of the impact of weather on mode choice the next chapter investigates the impact of weather on trip generation. Next, the results of the mode choice and trip making analysis are combined and applied to several climate change scenarios in order to assess the sensitivity of travel behaviour to change in weather. The last chapter highlights nature and magnitude of the potentially significant impact of weather on active transportation and points to some limitations and future research directions.

Chapter 2 Literature Review

Several variables help define the utility of the alternatives in any transportation mode choice analysis. Out-of-pocket cost and travel time of all feasible transportation alternatives are important characteristics in understanding trip-makers' behaviour. In addition to travel times and costs, researchers such as the Victoria Transportation Policy Institute (2009) and many others (Handy et al. 2002; Dill & Carr 2003; Nelson & Allen 2009; Cervero & Kockelman 1997; Cervero & Duncan 2003) in the field of active transportation have identified several socio-economic and built environment factors that influence walking and cycling mode choice significantly. Some of socioeconomic characteristics include car ownership, possession of drivers licence, gender, employment, income, and age. Significant built environment factors include land use patterns, street connectivity, topography, and cycling and walking facilities. Although these factors are introduced here as being significant to both walking and cycling, their impact on each of the two modes are quite different in many cases as discussed later.

More recently, with the aim of better predicting active transportation behaviour, researchers have been looking at less conventional factors that may influence active transportation mode choice. An example is Zing and Handy's work on cycling use and ownership (2008), which suggests that the effects of individual attitudes and social environment on bicycle ownership and use is even stronger than cycling infrastructure.

Occasionally some indicators for weather conditions or climate are incorporated in active transportation behaviour and mode choice studies such as those conducted by Dill & Carr (2003), Winters et al. (2007), and Parkin et al. (2008), amongst others. Depending on the nature of the study the level of detail of such indicators range from average annual temperatures and total annual amount of rainfall to detailed micro scale temperature, wind, humidity and precipitation conditions. Such studies can be grouped into two major categories according to the advantages and disadvantages that are faced with due to the type of data used. One group contains those looking at national travel behaviour data, which could be rich in socioeconomic variables but weak in detail on weather condition variables. The second group consists of local studies that usually involve count data. Such studies collect little data on trip-maker characteristics and characteristics of alternative modes, while the weather condition data associated with the counts can be quite detailed and elaborate. Examples of both types of work and the associated advantages and drawbacks are presented in the following paragraphs.

2.1 National or Regional Assessments of Impact of Weather on Active Transportation

It is difficult to draw strong conclusions about relationships between weather and non-motorized mode share without controlling for the more influential factors, namely socioeconomic characteristics and level of service variables. This is especially true at highly aggregate level of trip data, which consequently result in aggregate weather condition variables. Dill and Carr (2003) for instance, in their analysis of bicycle commuting in forty three large cities in the USA included few socioeconomic characteristics such as auto ownership, in addition to other variables such as bike/pedestrian funding and facilities. Aggregate weather variables such as number of rainy days per year and annual inches of rainfall were also included in the analysis. Although the former was found to be a significant for mode choice, its influence was shown to be very small. It is anticipated that temperature is also a significant variable and that the impact of precipitation is stronger than that suggested by Dill and Carr (2003); however it was not captured due to the aggregate nature of the weather data and limited socioeconomic variables.

A more recent study by Winters et al. (2007) looked at climate and socioeconomic characteristics on utilitarian cycling trends in fifty three Canadian cities. The 2003 Canadian Community Health Survey data used in this study is rich with socioeconomic characteristics such as age, gender, household income, education, student status and language. The trip data, however, is aggregate and at the city level only. Consequently, the climate data included in the analysis are general and include variables such as number of days/year below freezing temperature, or number of days/year with precipitation. In spite of this level of aggregation the study still finds that every 30-day increase in precipitation is associated with a 16% decrease in annual bicycle mode share, and every 30-day increase in freezing temperatures results in another 9% decrease in bicycle mode share.

The significant influence of rain and temperature on cycling, even at highly aggregated levels of data, is suggested by other researchers as well. Parkin et al. (2008) uses the census data for over three hundred districts in the UK to analyze commute cycling mode-share. Similar to the

Canadian example, the data used contains a good variety of socioeconomic characteristics while the climate data is limited to mean annual temperature and annual rainfall in millimetres. The results of the study point to a high negative elasticity of 0.655 for cycling mode share associated with amount of rainfall. Cycling mode share also has a positive elasticity of 0.703 to higher mean annual temperatures.

Van Berkim et al. (2006) conducted a quite thorough study on the impact of weather on urban travel demand in the Netherlands. Although this research is not specific to active transportation, cycling is considered a major mode of transportation next to private auto and transit in the Netherlands. By studying the Dutch National Mobility Survey (OVG) and corresponding daily weather conditions to trips in the survey they conclude that the reduction in bicycle use during adverse weather is accompanied by a modal shift from bicycle to car driver or passenger. Their results also suggest that seasonal influences (summer vs. winter) are less prominent than short term changes in precipitation conditions when looking at all modes. For the bicycle mode specifically however, mode share drops by about 5 percentage points in winter compared to summer and 4 percentage points in wet conditions compared to dry conditions. An online stated preference survey of 114 individuals is also conducted as a part of Van Berkim's study. The results of the survey suggest that about 50% of respondents postpone bike trips in rainy conditions and 22% cancel the trip all together in adverse weather. The survey further reveals that 23% of respondents change their mode of travel based on weather forecasts while 55% change their mode based on the actual observed weather conditions. There are however some limitations and disadvantages with stated preference surveys which are briefly discussed later.

Even at such high level of trip and weather condition aggregation, after controlling for the more primary factors, weather conditions are identified to be significant in the examples above. The aggregate nature of the data used however, inhibits further analysis into the interaction between weather variables and different demographic groups. Additionally, it is not possible to associate specific weather conditions with specific trips in order to observe behavioural change at the detailed level. Lastly, more detailed weather condition variables such as different temperature ranges, and different precipitation conditions would provide more insight into trip-makers' behaviour and response. Examples include identifying comfortable temperature thresholds, a potential non-linear relationship between cycling mode share and temperature, or interaction effects of temperature, wind and precipitation.

2.2 Location-Specific Analysis of Impact of Weather on Active Transportation

The second group of literature introduced below improves on some of the drawbacks highlighted above by collecting detailed weather data as a component of count surveys, but faces other data disadvantages.

One of the challenges with most count surveys is that little information is collected about the trip-makers' characteristics and the nature of the trip. Brandenburg et al (n.a.) for instance, in their investigation of commuting and recreational bicycle trips in Vienna, in absence of more trip details, assume that all AM and PM peak period bicycle counts were commuting trips and the remainder to recreational trips. Other information such as age, income, education, and student status is not captured at all in a count survey. At the same time, this method of data collection offers some advantages. Data for this study were collected at the entrance point to recreational cycling paths for a duration of one year. This made it possible to record microscale weather condition data on air temperature, vapour pressure, wind speed, cloud cover, and global radiation. By combining these with factors such as human activity and clothing insulation of observed trip makers the authors developed a thermal comfort index for their analysis. Results of this analysis points at the higher sensitivity of recreation cyclists to "bad" weather compared to commuters. Thomas et al. (2009) also conducted a similar count survey over many years at 16 cycling paths in the Netherlands and developed a daily "weather parameter" using temperature, wind, duration of sunshine and duration of rain data.

Another drawback to the more local studies is that the samples may not represent the entire population well since data collection is conducted at a few specific locations. Nankervis (1999) for instance conducted a study on the effect of weather on bicycle commuting in Melbourne, Australia by counting the number of parked bicycles at a university campus for two one-year periods in order to study changes in bicycle flow in different weather conditions and temperatures. The study complemented these data with a stated preference survey of students and staff at three university campuses. However, the studied sample is an atypical group in several significant aspects and results may not be transferable to non-student populations. Another limitation of this study is lack of data on sub-zero temperatures due to the climate of Melbourne. Nevertheless, the conclusions of this research suggest that while there is a decline in bicycle flows due to short-term and long term weather changes, student commuter cyclists are not easily dissuaded from cycling.

Stated preference surveys can be useful in gaining insight into people's perception of weather conditions, in addition to collecting data on hypothetical situations. However, such surveys come with disadvantages such as inefficient design of hypothetical scenarios and small and a typical samples. Cools et al. (2010) for instance recently conducted a stated preference survey of 350 people in Belgium in order to explore the affect of weather on travel behaviour, including mode choice. The small sample size inhibited the author to study the different modes individually; The general results, however, suggest that change in weather condition influences mode choice, especially across different trip purposes. Another interesting example of use of attitudinal surveys is the work of Bergstrom and Magnusson (2003) on the potential of transferring auto trips to bicycle trips during winter. As a part of this study one thousand employees of four major firms in Sweden were surveyed. The conclusions of the study suggest that it is possible to increase winter cycling mode share by 18% by improving winter bicycle path maintenance. They further suggest that this corresponds to a 6% decrease in auto mode share. However, the issue of sample bias applies to this study as well since the surveyed sample does not represent the whole population.

It is evident that while several researchers have taken various approaches in looking at the impact of weather conditions on cycling, there is a smaller number of studies on this impact on walking. One recent example is the work of Aultman-Hall et al. (2009). Pedestrian counts, along with temperature, wind, humidity and precipitation were collected for a period of one year for this study. The authors concluded that there is a large influence of weather on walking in the downtown area. They further suggest that this justifies efforts on policy programs and counter measures for walking in adverse weather. Several researchers have also looked at the effect of weather on walking speed (Daamen & Hoogendoorn 2003, Montufar, Arango, Porter, & Nakagawa 2007, Knoblauch, Pietrucha, & Nitzburg 1996), although with varying results. While the results of some researchers suggest that walking speeds increase in winter, others suggest the opposite.

2.3 Findings on the Impact of Weather on Overall Travel Behaviour

In addition to studies that are focused on active modes of transportation several researchers have looked at the impact of weather on travel as a whole, and on other modes such as transit and auto. Evidence of change in travel behaviour due to weather is reported in research conducted by Khattak and De Palma (1997). The research suggests that amongst the 50% of Brussels commuters who change some travel decision in adverse weather about a quarter change their mode, 60% change their departure time and 35% divert to an alternate route. More specifically, on the topic of the effect of weather on auto traffic volume several studies have looked at data provided by road counts. Maze et al. (2006), for instance, conclude that there is a traffic volume reduction of up to 20% in mild snow and 80% in strong snow with reduced visibility, compared to clear conditions. They also observe that commercial vehicles volume is much less sensitive to adverse weather compared to private auto volume. Other researchers such as Knapp et al. (2000) and Hanbali and Kuemmel (1992) conducted similar analysis on traffic volume suggesting traffic volume reductions in snow. Furthermore Ibrahim and Hall (1994) discovered a 10 to 20% reduction in traffic volumes in rain. Lastly, there has been some research on the impact of weather on transit ridership, although the results are not conclusive. Guo et al. (2007) conclude that good weather improves ridership while bad weather has a diminishing effect on transit ridership in Chicago. According to Khattak and De Palma (1997), however, the transit agency in Brussels reported higher levels of transit ridership during adverse weather.

Looking at the literature introduced in this section it is evident that weather has a significant and sometimes large impact on transportation, specifically on walking and cycling. There are, however, some gaps in the current state of research some of which will be addressed in this thesis. This involves including detailed weather conditions and using a large sample of travel behaviour rich in socioeconomic and level of service information of all modes. Such data is a good representation of the general population and allows for comparison of the sensitivity of different genders and age groups. Additionally, this allows for separating trips based on trip purpose which results in more accurate models. Availability of data on all major modes make it possible to investigate the impact of weather on walking, which has remained quite unexplored, compared to cycling.

Chapter 3 Data

3.1 Travel Survey Data

The travel data used to estimate the models presented in this paper is part of the 2001 Transportation Tomorrow Survey (TTS). The TTS is a trip diary survey of approximately 5% of the Greater Toronto Area residents 11 years of age and older that is conducted every 5 years (Data Management Group 2001). The data were collected between September 8th and December 16th of 2001 and May 8th to June 12th of 2002. Trips from five modes of auto driver, auto passenger, transit, walk and bicycle are included in the analysis. Although the 2006 TTS data is also available, the level of service information associated with the data is readily available for only the 2001 survey, which is why the 2001 data was used.

The socioeconomic information associated with the trip makers used in this study include number of persons in household, number of vehicles in household, age, gender, possession of a transit pass, possession of a driver's licence, employment status and student status. The trip characteristics that are included are trip purpose, zone of trip origin and destination, and time of trip.

As specified earlier, this study attempts to model behaviour of individuals who are not captive to a limited choice set of travel alternatives and have relatively easy access to all the five modes. This is to ensure that trip makers have the flexibility to switch between modes in adverse weather conditions. Therefore a set of constraints are applied to the sample. These are:

- Restrict sample to individuals with a driver's licence to ensure that the auto driver mode is feasible;
- Restrict sample to individuals living in households with at least one vehicle to ensure that the auto driver or passenger modes are feasible;
- Restrict trips to those with both origin and destination within the City of Toronto boundaries to ensure that some form of reliable public transit (bus, streetcar or subway) is available to trip maker;

- Restrict trips to those shorter than 20 km in Manhattan distance (estimated travel distance based on the grid-iron street pattern) to ensure slower modes of transportation are feasible options;

- Restrict the sample to home-based work trips so that skipping the trip under suboptimal conditions is less likely.

Another reason for limiting the sample to home-based work trips is that utilities of different travel modes are quite varied across different trip purposes and for home-based vs. non-home-based trips (Ortuzar 1983; Asensio 2002). As a result, only work trips originated from or destined to home are modelled here. Additionally, trips made by walk or cycle are only collected when the reported trip purpose is work or school. Table 3-1 illustrates a summary of sample size reductions as a result of the above constraints and the final resulting sample. Some 52% of households are eventually included in the modeled data after application of the various restrictions, corresponding to 34% of the individuals and 17% of the trips. The reason why these ratios are different and decreasing is that some of the restrictions, such as data cleaning steps, and restrictions on drivers licence ownership are only applied at the person level. Similarly, some data cleaning steps, in addition to restrictions on trip purpose, trip distance, and mode are only applied to trips only.

Table 3-1 TTS sample statistics at various stages of sample constraining

	Total TTS Sample for Toronto (Processed)	Home-based Work trips (% of total)	Trips less than 20 km (% of total)	At least one car in trip-maker's household (% of total)	trip maker possesses driver's license (% of total)	Resulting Estimated Sample (% of total)
Households	37582	25645 (68%)	33183 (88%)	30773 (82%)	33580 (89%)	19558 (52%)
Persons	71322	35875 (50%)	57712 (81%)	61274 (86%)	52804 (74%)	24188 (34%)
Trips	250665	65455 (26%)	128864 (51%)	174142 (69%)	155835 (62%)	43557 (17%)
Transit (mode share)	58270 (23%)	22248 (34%)	37975 (29%)	30433 (17%)	26525 (17%)	10603 (24%)
Bike (mode share)	3361 (1%)	1103 (2%)	2208 (2%)	1635 (1%)	2000 (1%)	612 (1%)
Walk (mode share)	18984 (8%)	4460 (7%)	14552 (11%)	11156 (6%)	5736 (4%)	2087 (5%)
Drive (mode share)	132758 (53%)	31977 (49%)	53681 (42%)	105269 (60%)	105611 (68%)	27142 (62%)
Passenger (mode share)	37292 (15%)	5666 (9%)	20450 (16%)	25649 (15%)	15963 (10%)	3113 (7%)

*the term "processed" refers to data cleaning and elimination of records with missing variables or unavailable level of service information

As mentioned in the introduction, in addition to the basic MNL model, the interaction between weather and age and weather and gender are explored through two sub models . This is achieved through breaking down the data by age groups and gender. Table 3-2 provides a summary of the data statistics for these two categorical variables.

Table 3-2 Sample breakdown by gender and age groups

		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total
		No. Of records (% of mode total)					
Gender	**Male**	4779 (45%)	424 (69%)	1030 (49%)	16666 (61%)	979 (31%)	23878 (55%)
	Female	5824 (55%)	188 (31%)	1057 (51%)	10476 (39%)	2134 (69%)	19679 (45%)
Age	**below 25**	1032 (10%)	35 (6%)	216 (10%)	1414 (5%)	406 (13%)	3103 (7%)
	25 to 39	4914 (46%)	313 (51%)	936 (45%)	10330 (38%)	1283 (41%)	17776 (41%)
	40 to 55	3701 (35%)	227 (37%)	689 (33%)	11315 (42%)	1095 (35%)	17027 (39%)
	55 to 65	888 (8%)	35 (6%)	223 (11%)	3668 (14%)	300 (10%)	5114 (12%)
	above 65	68 (1%)	2 (0%)	23 (1%)	415 (2%)	29 (1%)	537 (1%)
total		**10603**	**612**	**2087**	**27142**	**3113**	**43557**

3.2 Level of Service Data

Level of service information was approximated from several sources. Assumptions and estimations had to be made with regards to some of the information. The following is a list of level of service variables and their corresponding source of data:

- Auto driver cost: calculated based on travel distance, average fuel consumption and fuel cost estimates from 2001;

- Parking cost: Average daily parking costs by traffic zone were obtained for the City of Toronto based on their survey of off-street daily parking charges;

- Transit fare: determined based on trip makers' transit pass ownership, age and student status using reported 2001 transit fares for Toronto (The Toronto Transit Commission 2009);

- Transit in-vehicle, walk and wait times: obtained from an EMME/2 transit assignment for the morning peak period. Assignment parameters and assumptions are documented in (Miller 2001). Wait times are computed as half the headway of services serving each stop and walk access/egress times are based on a walking speed of 4 km/hr. At the time of compiling the data off-peak and afternoon peak networks for the GTA were not available and so morning peak period travel times were used for travel in all time periods;

- Walk travel time: calculated based on Manhattan travel distance and walking speed of 4 km/hr;
- Bicycle travel time: calculated based on Manhattan travel distance and cycling speed of 16 km/hr;
- Auto in-vehicle travel time: determined by conducting 24 one-hour user equilibrium traffic assignments using the EMME/2 modelling software and TTS travel demand data.
- Land use variables
    - Arterial density: ratio of kilometres of arterial roads over kilometre of total road in the traffic analysis zones (Coleman 2002)
    - Intersection density: number of intersections (excluding cul-de-sacs) per square kilometre in the traffic analysis zones (Coleman 2002)
    - Population density: population per square meter of land

For the arterial density, intersection density and population density measures indicated above, the average of measurements for the origin and destination zones of a trip is used. This is best justified for the walk mode, where most trips take place either within one zone or between two adjacent zones, or for transit trips, where mainly the built environment characteristics of the access and egress zones, where walking takes place, is of significance. For the bicycle mode the built environment characteristics of all the zones that a bicycle trip route would go through are of significance. However, the bicycle route was not known.

Out-of-pocket cost (i.e. direct and immediate expenditure made at the time of travel or at the gas station) for auto passenger, walk and bicycle are assumed to be zero. Similarly out of pocket transit cost for transit pass holders is assumed to be zero.

A measure of density of bicycle lanes within each traffic zone would have been a useful addition to the level of service characteristics as a bikability indicator. The bicycle road network in Toronto has been expanding rapidly in the last number of years and the authors were unable to find an accurate enough bicycle lane provision time-line in order to determine the available network in 2001. Topographical information such as hilliness (Scarf & Grehan 2005), or slope gradient (Cervero & Duncan 2003) are also known to be important walkability and bikability measures. However, given Toronto's relatively flat topography, especially in the East-West direction, and lack of bicycle route information, the authors chose not to include this variable.

3.3 Danforth Bicycle Lane Count Data

The Traffic Data Centre of the City of Toronto has been collecting hourly bicycle count data in both directions along the Danforth bicycle lane using two active infrared sensors at the intersection of Bloor Street East and Castle Frank Crescent since January 1999 (See Figure 3-1 for location of counts). Active infrared sensors are optimum for distinguishing between pedestrian and cyclists. The advantage that this dataset offers compared to the TTS data is that counts are conducted year round. Therefore, although the data were not used for the mode choice model developed in this thesis, preliminary analysis using 9 years of the data provides useful insight into the behaviour of cyclists in various weather conditions. Table 3-3 displays the average hourly volume and the number of hours of data in either direction during the morning and afternoon peak hour. The higher morning westbound volume and afternoon eastbound volume on weekdays suggest that the route is commonly used by commuters accessing the city centre.

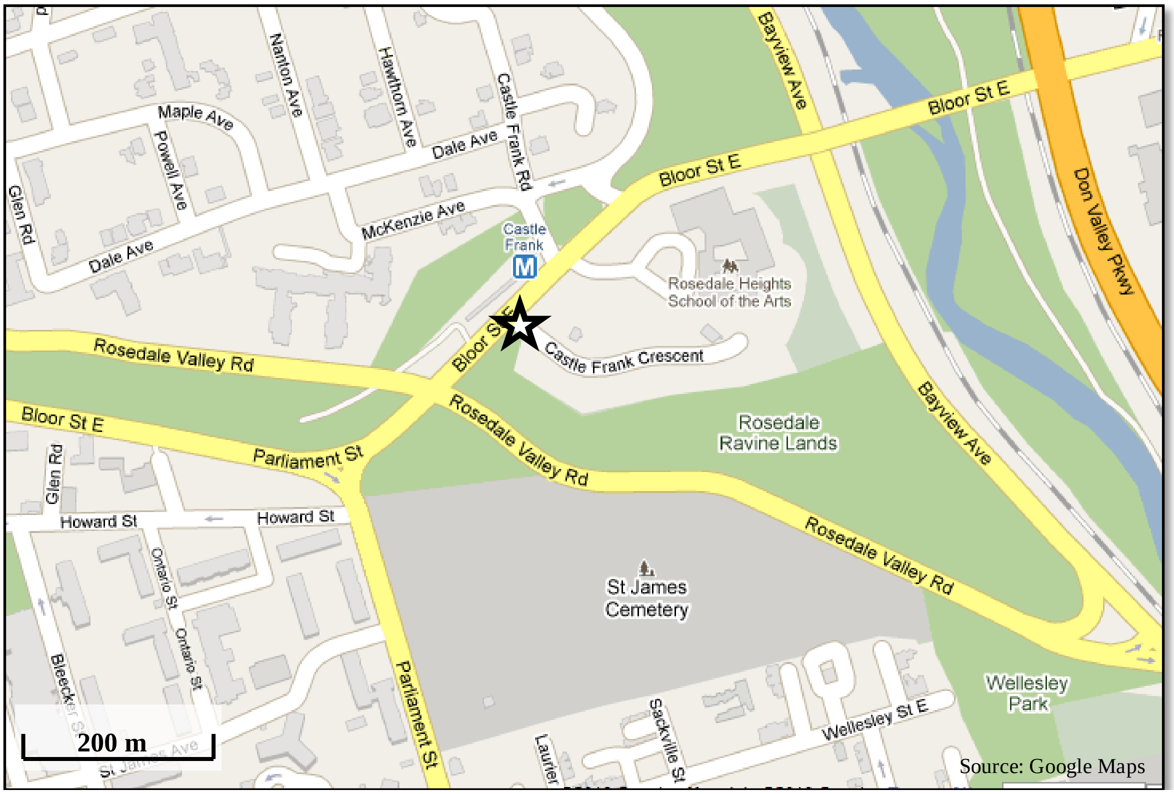

Figure 3-1 Location of bicycle counts

Table 3-3 Danforth bicycle lane bicycle count data statistics

Direction	Time	Average Hourly Volume (number of hourly records)	
		Weekend	Weekday
Eastbound (outbound)	AM Peak	20 (635)	40 (1505)
	PM Peak	56 (635)	148 (1505)
Westbound (inbound)	AM Peak	34 (670)	157 (1643)
	PM Peak	48 (670)	56 (1643)

3.4 Weather Data

The Transportation Tomorrow Survey data were collected between September 8th and December 16th of 2001 and May 8th to June 12th of 2002. The database contains information on week of the year and day of the week for which each individual is surveyed and the time of each trip, approximated by the respondent, to the nearest 15 minutes. Similarly, exact date and time of the Danforth bicycle lane hourly counts were available. This detailed information makes it possible to correspond the exact time of the each trip of the TTS and each hourly bicycle count of the Danforth bicycle lane data with the weather conditions at that time.

Hourly weather data corresponding to the period of the TTS survey and Danforth bicycle lane count data, collected at the Toronto Pearson International Airport weather station, were purchased from Environment Canada (Environment Canada 2008). The database includes information on temperature, wind speed, humidity and sky conditions. A small number of temperatures and sky conditions were reported as “missing”. These fields were input based on the reported weather for the previous and the next hour, when available. Missing temperatures, for instance, were calculated as the average of the temperature of the previous and next hour. Missing sky conditions were only interpolated when the sky condition of the previous and next hour were the same. The trip data corresponding to the remaining missing weather conditions had to be eliminated from the data set. This constitutes a very small number of trips. Temperatures are adjusted for wind-chill and humidex based on equation 1 through 4 provided by Environment Canada (Environment Canada 2010) and using the provided wind speed or humidity level for a given time.

<u>Humidex</u>

$$T_{\mathrm{humidex}} = (T_a) + h, \qquad (1)$$

where T_a is the actual air temperature in ^{o}C,

$$h = (0.5555) \times (v - 10.0), \qquad (2)$$

and, v is vapour pressure in hPa (mbar), given by:

$$v = 6.11 \times e^{\left[5417.753 \times \left(\frac{1}{273.16} - \frac{1}{dewpoint}\right)\right]}. \qquad (3)$$

<u>Wind-Chill</u>

$$T_{wind-chill} = 13.12 + 0.6215T_a - 11.37V^{0.16} + 0.3965T_aV^{0.16}, \qquad (4)$$

where T_a is the actual air temperature in ^{o}C and v is wind speed in km/hr.

Several verbal descriptions are used for the sky conditions in the raw weather data. These were reduced to five mutually exclusive categories of clear, cloud, rain, shower and snow for the TTS data. Table 3-4 shows the correspondence between the verbal description of sky conditions and the sky condition categories used in the model.

Table 3-4 Categorization of sky condition descriptions

Model Category	**Environment Canada Data**
Clear	Clear
Cloud	Cloud, haze, fog
Rain	Rain, freezing drizzle, freezing rain
Shower	Rain shower, thunderstorm
Snow	Snow, snow showers, ice pellets, snow grains, ice crystals, snow pellets

Table 3-5 provides a breakdown of the estimated TTS sample by these sky conditions and nine temperature categories.

Since the available weather data are in one-hour intervals TTS Trip times were rounded up to the nearest hour if past the half hour point, or rounded down to the nearest hour if during the first half of the hour. Temperature and sky conditions were then associated with each trip based on the exact date and time of observed trips after adjusting for daylight savings time.

Since the TTS data collection period was during the Fall and Spring seasons, very few observations are made in snowy conditions. As a result the snow variable was not included in the model specifications. This also eliminates complications with high correlation between the snow and the sub-zero temperatures. In addition to the temperature categories and sky conditions reported above, wind speed data were also available and used in the analysis. Wind speeds range between 0 and 70 km/hr, with an average of 17 km/hr. Additionally, the sunshine angle was calculated for all clear days for each trips based on the exact time of the trip. An angle of zero was considered for all night-time hours and non-clear sky conditions. As evident in the model results presented in the upcoming chapters, the sun angle variable did not come out to be significant for any of the modes and was therefore not included in the final model.

Table 3-5 TTS sample breakdown by different weather variables

		Transit number (% of total)	Bike number (% of total)	Walk number (% of total)	Auto Driver number (% of total)	Auto Passenger number (% of total)
Temperature (C)	**Below 0**	260 (2.5%)	12 (2%)	61 (2.9%)	760 (2.8%)	107 (3.4%)
	1 to 5	2295 (21.6%)	124 (20.3%)	435 (20.8%)	6009 (22.1%)	770 (24.7%)
	6 to 10	3329 (31.4%)	165 (27%)	706 (33.8%)	8704 (32.1%)	1022 (32.8%)
	11 to 15	2683 (25.3%)	159 (26%)	503 (24.1%)	6779 (25%)	708 (22.7%)
	16 to 20	1548 (14.6%)	118 (19.3%)	309 (14.8%)	3809 (14%)	404 (13%)
	21 to 25	401 (3.8%)	27 (4.4%)	57 (2.7%)	860 (3.2%)	78 (2.5%)
	26 to 30	52 (0.5%)	5 (0.8%)	9 (0.4%)	147 (0.5%)	14 (0.4%)
	31 to 35	14 (0.1%)	1 (0.2%)	2 (0.1%)	39 (0.1%)	6 (0.2%)
	above 35	21 (0.2%)	1 (0.2%)	5 (0.2%)	35 (0.1%)	4 (0.1%)
	Total	**10603**	**612**	**2087**	**27142**	**3113**
Sky Conditions	**clear**	3098 (29.2%)	183 (29.9%)	572 (27.4%)	7876 (29%)	921 (29.6%)
	cloud	5963 (56.2%)	367 (60%)	1178 (56.4%)	15498 (57.1%)	1759 (56.5%)
	rain	1120 (10.6%)	45 (7.4%)	233 (11.2%)	2732 (10.1%)	319 (10.2%)
	showers	416 (3.9%)	17 (2.8%)	104 (5%)	1015 (3.7%)	112 (3.6%)
	snow	6 (0.1%)	0 (0%)	0 (0%)	21 (0.1%)	2 (0.1%)
	Total	**10603**	**612**	**2087**	**27142**	**3113**

Table 3-6 and Table 3-7 summarize the number of bicycle trips collected on the Danforth bicycle lane in various temperatures and sky conditions during the AM and PM peak hours, broken down by weekdays vs. weekends/holidays for the eastbound and westbound direction, respectively. Due to the large sample size in this case sky condition categories are more disaggregate here compared to the TTS data.

Table 3-6 Danforth bicycle lane count breakdown by different weather variables - eastbound

		Weekday		Weekend	
		AM	PM	AM	PM
		Number of observed cyclists (% of total)		Number of observed cyclists (% of total)	
Temperature	**below -25**	212 (0.4%)	100 (0%)	29 (0.2%)	35 (0.1%)
	-25 to -15	965 (1.6%)	1206 (0.5%)	254 (1.9%)	383 (1%)
	-5 to -14	4534 (7.7%)	9868 (4.5%)	1016 (7.4%)	1632 (4.2%)
	-4 to 0	5413 (9.2%)	11187 (5.1%)	902 (6.6%)	2170 (5.6%)
	1 to 5	7336 (12.5%)	17640 (8%)	1368 (10%)	2359 (6.1%)
	6 to 10	4731 (8%)	11769 (5.4%)	1003 (7.3%)	1877 (4.9%)
	11 to 20	24410 (41.4%)	67753 (30.8%)	5462 (40%)	12137 (31.6%)
	21 to 30	8179 (13.9%)	67927 (30.9%)	2668 (19.5%)	11222 (29.2%)
	above 30	3132 (5.3%)	32438 (14.8%)	967 (7.1%)	6634 (17.3%)
	Total	**58,912**	**219,888**	**13,669**	**38,449**
Sky Condition	**clear**	48103 (81.7%)	193905 (88.2%)	11713 (85.7%)	35412 (92.1%)
	rain	1515 (2.6%)	4920 (2.2%)	400 (2.9%)	673 (1.8%)
	rain shower	1276 (2.2%)	6630 (3%)	242 (1.8%)	528 (1.4%)
	thunderstorm	118 (0.2%)	2064 (0.9%)	61 (0.4%)	352 (0.9%)
	drizzle	584 (1%)	836 (0.4%)	50 (0.4%)	112 (0.3%)
	fog	2794 (4.7%)	2285 (1%)	459 (3.4%)	142 (0.4%)
	snow	1188 (2%)	2684 (1.2%)	271 (2%)	461 (1.2%)
	haze	3242 (5.5%)	6477 (2.9%)	443 (3.2%)	769 (2%)
	other	92 (0.2%)	87 (0%)	30 (0.2%)	0 (0%)
	Total	**58,820**	**219,801**	**13,639**	**38,449**

Table 3-7 Danforth bicycle lane count breakdown by different weather variables - westbound

		Weekday		Weekend	
		AM	PM	AM	PM
		Number of observed cyclists (% of total)		Number of observed cyclists (% of total)	
Temperature	**below -25**	765 (0.3%)	84 (0.1%)	117 (0.5%)	32 (0.1%)
	-25 to -15	3533 (1.4%)	1217 (1.3%)	351 (1.4%)	457 (1.4%)
	-5 to -14	13892 (5.4%)	4985 (5.5%)	1678 (6.9%)	1519 (4.5%)
	-4 to 0	20187 (7.9%)	4518 (5%)	1714 (7%)	1912 (5.7%)
	1 to 5	27368 (10.7%)	7035 (7.7%)	1999 (8.2%)	2075 (6.2%)
	6 to 10	19960 (7.8%)	4310 (4.7%)	1340 (5.5%)	1698 (5%)
	11 to 20	113687 (44.3%)	26486 (29.1%)	10847 (44.5%)	10344 (30.7%)
	21 to 30	43896 (17.1%)	27489 (30.2%)	4880 (20%)	9714 (28.9%)
	above 30	13599 (5.3%)	14860 (16.3%)	1473 (6%)	5916 (17.6%)
	Total	**256,887**	**90,984**	**24,399**	**33,667**
Sky Condition	**clear**	214318 (83.4%)	80575 (88.6%)	21248 (87.1%)	30906 (91.8%)
	rain	6352 (2.5%)	2333 (2.6%)	523 (2.1%)	667 (2%)
	rain shower	5974 (2.3%)	2501 (2.7%)	326 (1.3%)	576 (1.7%)
	thunderstorm	802 (0.3%)	687 (0.8%)	135 (0.6%)	56 (0.2%)
	drizzle	1285 (0.5%)	431 (0.5%)	113 (0.5%)	108 (0.3%)
	fog	10637 (4.1%)	548 (0.6%)	790 (3.2%)	200 (0.6%)
	snow	3670 (1.4%)	1339 (1.5%)	419 (1.7%)	504 (1.5%)
	haze	13627 (5.3%)	2494 (2.7%)	829 (3.4%)	650 (1.9%)
	other	222 (0.1%)	76 (0.1%)	16 (0.1%)	0 (0%)
	Total	**256,665**	**90,908**	**24,383**	**33,667**

Chapter 4 Empirical Analysis of Bicycle Count Data

Although the focus of this thesis is developing a weather sensitive mode choice model some empirical analysis of bicycle count data is performed and presented here. The advantage of this analysis over the mode choice model is that the count data were collected year-round over 9 years, as described earlier in section 3.3. The data cover very cold and very hot temperatures in addition to snowy conditions, which are not captured in the TTS survey. The nature of the data makes it possible to compare the influence of various sky conditions and temperature categories on commuter and recreational cycling.

The sky conditions analysed here include clear, rain, rain shower, thunderstorm, drizzle, fog, snow and haze. Moreover, the temperatures, ranging from -35 to 43^{o}C (adjusted for wind chill and humidex), are categorized into nine temperature groups. All temperature categories and sky conditions are introduced into the linear regression as dummy variables.

4.1 Methodology

The analysis presented here includes multivariate linear regression models developed for several different data sets. These data sets include eastbound (towards the city centre) and westbound (away from city centre) travel separated by morning (AM) and afternoon/evening (PM) peaks and weekdays and weekends/holidays. Separating weekend and weekday counts is an attempt to analyze commuter and recreational cycling behaviour separately, since it is expected that weather conditions have different impacts on these two trip purposes. AM and PM peak data and eastbound and westbound data are distinguished from one another in order to capture what are assumed to be commuter cyclists who travel westward towards the city centre in the morning and travel back to their place of residents eastward in the afternoon/evening. Although commuter vs. recreational trips are distinguished here based on the day of the week it should be noted that not all weekday cyclists are commuters, nor are all weekend cyclists recreational riders.

In the regression of the weekday PM peak travel, in addition to including temperature and sky conditions corresponding to actual time of travel in the afternoon/evening, the weather conditions corresponding to the morning of the same day are also included as variables. This is based on the assumption that choosing the bicycle mode for the journey back home is only possible if the bicycle was used in the morning. Secondly, it is anticipated that it is less of of an inconvenience to arrive at home wet or sweaty in the evening compared to arriving wet to work in the morning. Therefore, including the morning conditions in addition to the afternoon conditions is expected to help explain such assumptions.

A 95% confidence level was used as the significance threshold and all variables not meeting this criterion were dropped.

4.2 Results

Linear regression results for 3 different sets of data are discussed here. These include weekday AM peak westbound (Table 4-1), weekday PM peak eastbound (Table 4-3) and weekends/holiday AM peak for westbound (Table 4-2). A regression model is only estimated for the weekend flows that correspond to the weekday flows discussed here. The PM peak results for weekends/holidays were very similar to that of the AM Peak and are therefore not included.

About 65% of variability of weekday AM peak hourly trip volumes, 72% variability of weekday PM peak hourly trips volume and between 32 to 52% of variability in weekends/holidays hourly volume is captured by the regression models. The low adjusted R^2 value for weekends/holidays trips maybe due to the fact that variability of leisure cycling volumes depends very much on weekend and holiday events around the area and in destinations to the east and west of the location of data collection rather than weather. This is compared to the more constant commute cycling flow, which is generally headed towards the city centre in the morning and away from the city centre in the evening. The R^2 values for weekday regressions are relatively higher. The larger value for the PM regression compared to the AM regression is most probably due to inclusion of both AM and PM weather conditions.

Table 4-1 and Table 4-2 provide the regression results for weekday and weekend AM peak westbound (towards city centre) traffic, respectively. Figure 4-1 and Figure 4-2 display the relative magnitude of the estimated coefficients corresponding to sky conditions and temperature categories, respectively. Insignificant values are indicated on each figure by using the word “insignificant” in the place of the bar corresponding to the coefficient. Rain has the largest negative influence on commuter cycling volumes, followed by rain shower, thunderstorm, drizzle, fog, snow and haze, in descending order. It is interesting to see that more severe precipitations such as thunderstorms have a smaller influence than rain. This is potentially because rain events are longer in duration while thunderstorms arrive mostly by surprise and are expected to stop shortly. Additionally, it is interesting to see that snow ranks very low amongst the sky conditions in terms of magnitude of negative influence. It is therefore anticipated that the drop in winter cycling is mostly due to colder temperatures than snowy conditions. The magnitudes of sky condition coefficients for the weekend regression are, as expected, smaller than those for the weekday regression. Only fog, rain shower, and rain appear to be significant to weekend trips. In addition, the coefficients for these three variables do not follow the trend evident in weekday trips.

Table 4-1 Weekday AM peak westbound regression results

	Coefficient	Standard Error	t-stat	P>t	[95% Confidence Interval]	
clear			Reference category			
drizzle	-61.1	13.324	-4.58	0	-87.2	-34.9
fog	-54.7	5.836	-9.38	0	-66.2	-43.3
haze	-18.9	6.187	-3.06	0.002	-31.1	-6.8
rain	-72.8	6.456	-11.28	0	-85.5	-60.2
rain shower	-67.6	7.923	-8.53	0	-83.1	-52.1
snow	-19.6	6.802	-2.88	0.004	-33	-6.3
thunderstorm	-63.1	22.804	-2.77	0.006	-107.9	-18.4
below -25	-32.3	11.656	-2.77	0.006	-55.1	-9.4
-25 to -15	-18.1	6.933	-2.61	0.009	-31.7	-4.5
-5 to -14			Reference category			
-4 to 0	46.5	5.181	8.97	0	36.3	56.6
1 to 5	87.1	5.307	16.41	0	76.7	97.5
6 to 10	119.7	6.119	19.56	0	107.7	131.7
11 to 20	154.3	4.39	35.16	0	145.7	163
21 to 30	169.4	5.319	31.85	0	159	179.9
above 30	152.1	7.449	20.43	0	137.5	166.8
_cons	69.6	3.763	18.5	0	62.2	77

Source	SS	df	MS		
Model	7486438.5	15	499095.9	Number of observations	1603
Residual	4085181.2	1587	2574.153	F(15, 1587)	193.89
Total	11571620	1602	7223.233	Prob > F	0
				R-squared	0.647
				Adj R-squared	0.6436
				Root MSE	50.736

Table 4-2 Weekend/Holiday AM peak westbound regression results

	Coefficient	Standard Error	t-stat	P>t	[95% Confidence	Interval]
clear			Reference category			
drizzle	dropped					
fog	-13.7	2.512	-5.45	0	-18.6	-8.7
haze	dropped					
rain	-8.8	3.317	-2.95	0.003	-14.7	-2.9
rain shower	-14.2	4.106	-3.45	0.001	-22.2	-6.1
snow	dropped					
thunderstorm	dropped					
below -25	dropped					
-25 to -15	dropped					
-5 to -14			Reference category			
-4 to 0	9.2	2.158	4.39	0	5.1	13.3
1 to 5	13.7	2.13	6.42	0	9.5	17.8
6 to 10	19.1	2.614	7.3	0	13.9	24.2
11 to 20	31.9	1.623	19.74	0	28.7	35.1
21 to 30	34.9	1.943	17.99	0	31.1	38.7
above 30	37.8	2.96	12.76	0	32.0	43.6
_cons	15.3	1.334	11.55	0	12.7	17.9

Source	SS	df	MS		
				Number of observations	710
				F(15, 1587)	64.8
Model	152775.48	12	12731.29	Prob > F	0
Residual	136937.04	697	196.4663	R-squared	0.5273
Total	289712.52	709	408.6213	Adj R-squared	0.5192
				Root MSE	14.017

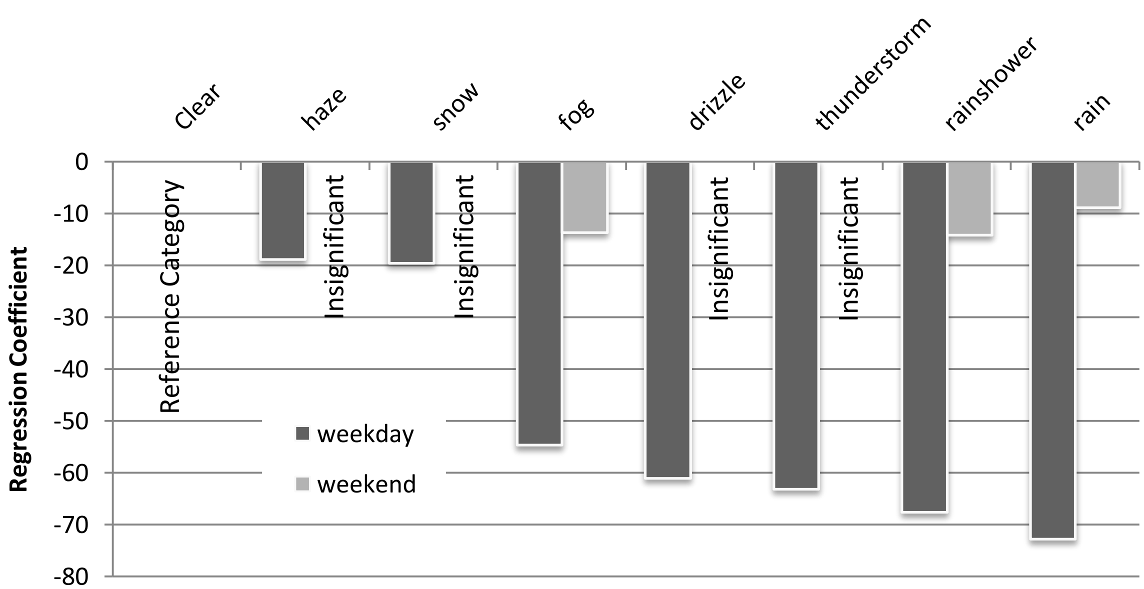

Figure 4-1 AM peak hour regression coefficients for weekday and weekend sky conditions

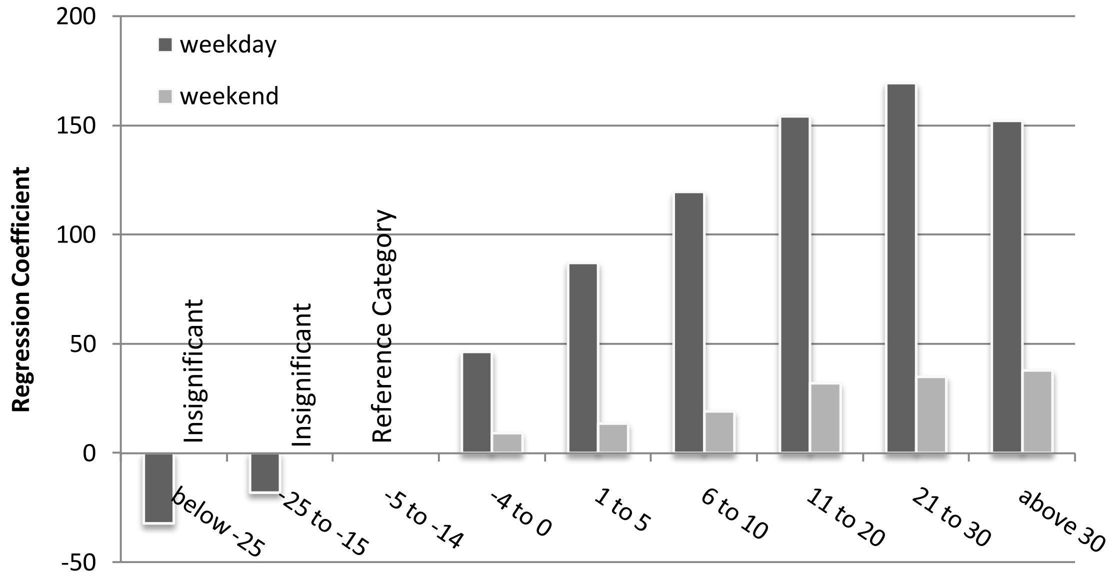

Figure 4-2 AM peak hour regression coefficients for weekday and weekend temperature categories

Temperature effects on both commuter and recreational trips are similar, although smaller in magnitude for leisure trips. The exception is that the coefficient drops at very high temperatures for commuter trip, while leisure trips volumes continue to grow with temperature increase past the 30^{o}C mark. This is probably because commuters do not have as much flexibility in clothing options in order to make hot temperatures more bearable while leisure riders do.

The commuter versus leisure regression comparison for the PM peak hour is very similar to that of the AM peak hour discussed above and is therefore not discussed here. Table 4-3 provides the regression results for weekday eastbound (away from city centre) PM peak traffic. For this weekday regression coefficients are estimated for sky condition and temperature variables corresponding to both the actual time of trips and the morning of each trip. Figure 4-3 and Figure 4-4 graphically display the relative magnitude of the AM and PM coefficients for sky condition and temperature variables, respectively.

Table 4-3 Weekday PM peak eastbound regression results

		Coefficient	Standard Error	t-stat	P>t	[95% Confidence Interval]	
PM – Actual time of travel	**clear**	Reference category					
	drizzle	dropped					
	fog	-32.2	9.502	-3.39	0.001	-50.8	-13.5
	haze	dropped					
	rain	-30.9	7.101	-4.35	0	-44.8	-17.0
	rain shower	-22.5	7.593	-2.97	0.003	-37.4	-7.6
	snow	-12.6	6.690	-1.88	0.06	-25.7	-0.5
	thunderstorm	-42.8	14.215	-3.01	0.003	-70.7	-14.9
	below -25	dropped					
	-25 to -15	dropped					
	-5 to -14	Reference category					
	-4 to 0	dropped					
	1 to 5	33.7	7.161	4.71	0	19.7	47.8
	6 to 10	51.3	8.702	5.89	0	34.2	68.3
	11 to 20	80.1	8.522	9.39	0	63.3	96.8
	21 to 30	113.4	9.517	11.92	0	94.7	132.1
	above 30	101.2	10.945	9.25	0	79.7	122.7
AM – Morning of the same day	**clear**	Reference category					
	drizzle	-42.7	11.29	-3.79	0	-64.9	-20.6
	fog	-43.4	5.77	-7.53	0	-54.8	-32.1
	haze	-19.5	6.33	-3.08	0.002	-31.9	-7.1
	rain	-54.1	6.52	-8.31	0	-66.9	-41.4
	rain shower	-45.5	8.30	-5.49	0	-61.8	-29.2
	snow	-16.6	6.59	-2.51	0.012	-29.5	-3.6
	thunderstorm	-62.6	27.84	-2.25	0.025	-117.2	-8.0
	below -25	dropped					
	-25 to -15	dropped					
	-5 to -14	Reference category					
	-4 to 0	26.1	5.863	4.45	0	14.6	37.6
	1 to 5	36.8	7.058	5.21	0	23.0	50.7
	6 to 10	45.3	8.517	5.32	0	28.6	62.1
	11 to 20	72.8	8.483	8.58	0	56.1	89.4
	21 to 30	77.3	9.968	7.75	0	57.7	96.8
	above 30	76.1	12.052	6.31	0	52.4	99.7
	_Const	58.3	4.507	12.93	0	49.4	67.1

Source	SS	df	MS		
				Number of observation	1462
				F(28, 1433)	132.51
Model	8416999.1	28	300607.1	Prob > F	0
Residual	3250952.4	1433	2268.634	R-squared	0.7214
Total	11667952	1461	7986.278	Adj R-squared	0.7159
				Root MSE	47.63

Results show that while sky condition coefficients for the morning and afternoon trips follow the same general trend, conditions of the morning of the day of travel are more influential than those of the actual time of travel. In the case of haze and drizzle conditions PM coefficients did not come out to be significant at all, while the AM coefficients did.

Contrary to the sky condition results, when looking at the coefficients for the top four temperature categories the coefficients corresponding to the actual time of trip are larger than those for the morning of the trip. AM temperatures below -15^{o}C and PM temperature below 0^{o}C come out to be insignificant. The general trends are similar to those observed for the AM peak regression suggesting that warmer temperatures have a larger positive influence on cycling numbers up to the 21 to 30^{o}C category, while the above 30^{o}C category becomes slightly less attractive again.

While the results of the regression analysis are interesting and provide an indication of the level of influence of temperature the various sky conditions it is not possible to make further conclusions about how different demographics are influenced by weather. Additionally, it is important to know the characteristics of other modes available to trip makers in order to further investigate the question at hand. The multinomial logit model described in the following chapters addresses these factors.

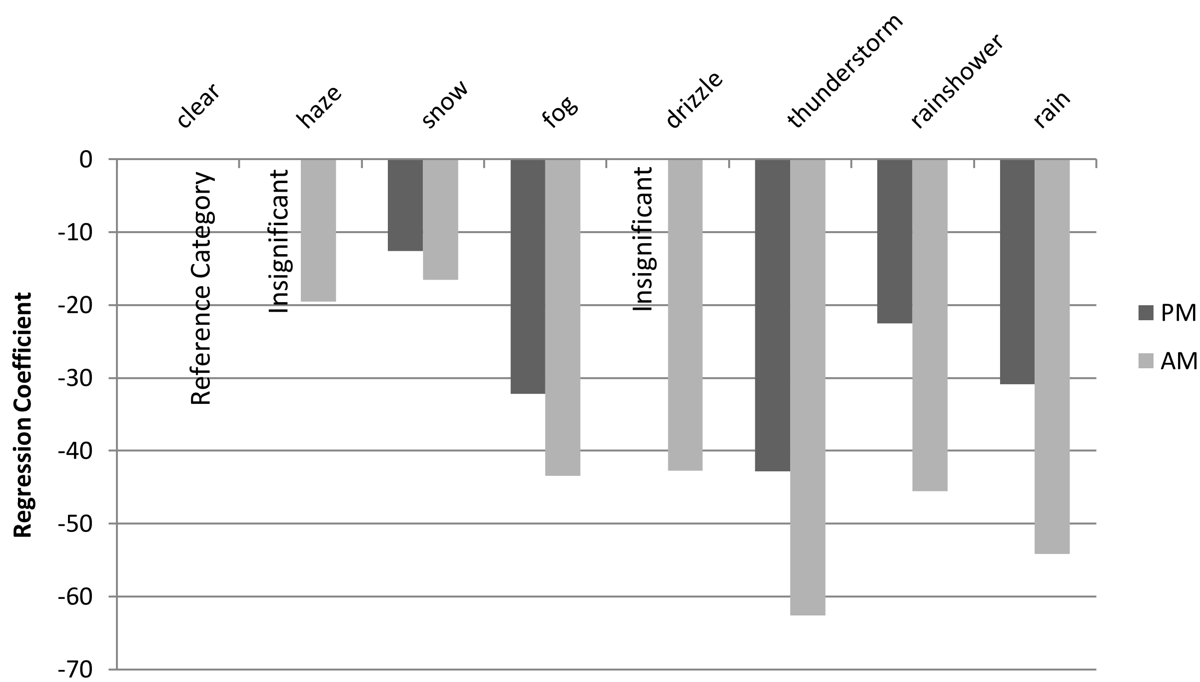

Figure 4-3 Eastbound PM peak hour regression coefficients for sky conditions of time of travel (PM) and morning of travel (AM)

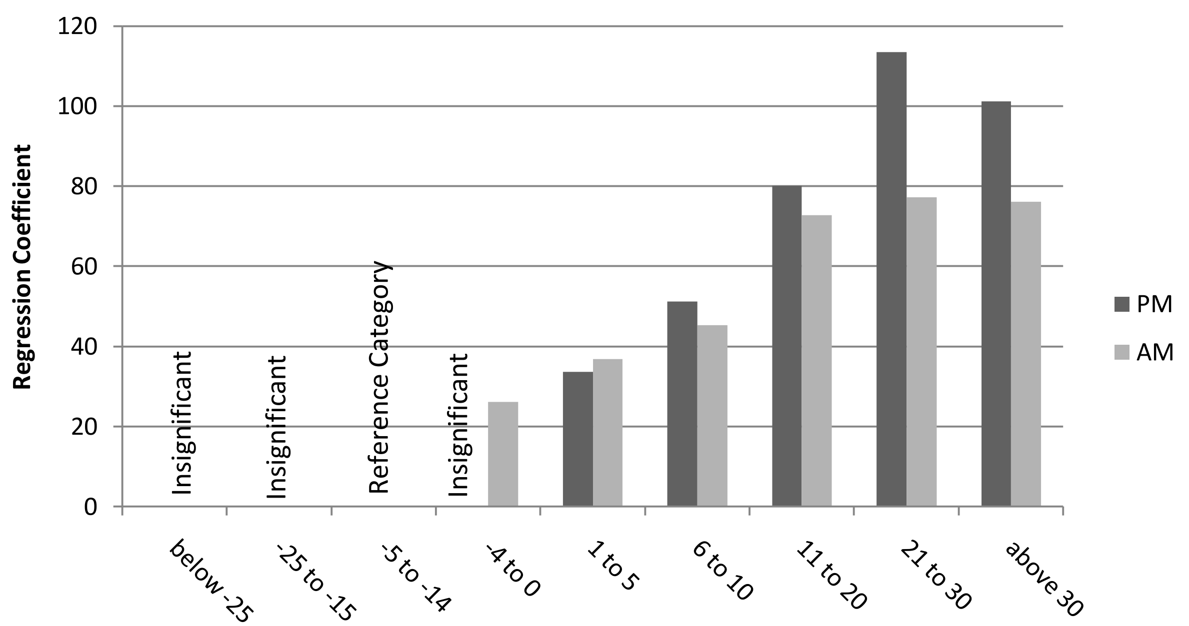

Figure 4-4 Eastbound PM Peak hour regression coefficients for temperature at time of travel (PM) and morning of travel (AM)

Chapter 5 Mode Choice Modelling

5.1 Theory

The decision to take one mode of travel over others is commonly treated as a utility maximization process. In such a process, the trip maker is assumed to be perfectly rational and by weighing the positives and negatives of all modes chooses the mode that maximizes net utility. In order to analyze the impact of weather conditions on the decision to walk and bike, this research relies upon the utility maximization theory in developing a multinomial logit model (MNL) of mode choice. Furthermore, based on the hypothesis that non-motorized travel modes share certain unobserved characteristics the nested logit modelling structure, described later, is also explored.

For the basic MNL model, U_{it} , the latent utility of alternative *i* for person *t* is formulated as

$$U_{it} = \beta_i X_{it} + \varepsilon_{it} = V_{it} + \varepsilon_{it} , \tag{5}$$

where X_{it} is the vector of relevant explanatory variables and β_i is a set of parameters or weights for each attribute described in X_{it}.. Therefore V_{it} is the observed utility and ε_{it} is a random error term corresponding to unobserved component of the individual's latent utility.

The probability of person *t* choosing mode *i* amongst a set of mutually exclusive feasible alternatives A_t is formulated as

$$P_t(i \mid A_t) = P(U_{it} \geq U_{jt}, \forall j \neq i, i, j \in A_t) \tag{6}$$

The logit model assumes that the error terms, ε_{it}, is independently and identically distributed. This is known as the independence of irrelevant alternatives (IIA) property and sets a major constraint in MNL models by implying that the error terms are independently and identically distributed. Under these assumptions the probability of individual t choosing alternative i is given by

$$P_{it} = \frac{e^{V_{it}}}{\sum_{j} e^{V_{ji}}} \tag{7}$$

As mentioned above, the IIA property implies that the error terms of all alternatives in a MNL model are independently distributed. However, there are situations in which certain alternatives share important, unobservable qualities.

More specifically, for the case of modelling non-motorized travel modes, the hypothesis is that the walk and bike modes are similar to one another in factors that are not captured by the variables included in the model specification. Similarity, we speculate that there may be certain shared unobservable characteristics amongst motorized modes as well. In order to reflect this relationship amongst modes in the mode choice model the nested modelling structure is considered.

In a nested logit model, correlation of the unobserved characteristics is allowed among lower level choices under the same grouping, allowing them to share some common attributes based on their grouping. Figure 5-1 illustrates a hypothetical two-level nested structure. Alternatives 1 and 2 are grouped together under Nest 1 based on the assumption of the modeller that they share certain unobservable characteristics. Similarity, Alternatives 3 and 4 are grouped under Nest 2. The nests are known as upper level choices, while the alternatives are the lower level choices. The upper level describes the shared utility component while the lower level describes the specific utility component.

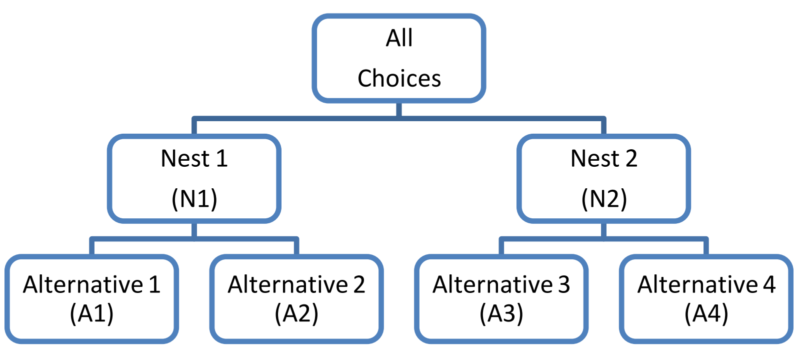

Figure 5-1 Graphical Representation of Nested Modelling Structure

The probability of an individual choosing upper level choice *N* is given by

$$P_N = \frac{e^{V_{it} + \Phi I_N}}{\sum_{N'} e^{V_{N'} + \Phi I_{N'}}}, \tag{8}$$

and the probability of an individual choosing lower level alternative A, given that he/she has chosen the upper level choice N is given by

$$P_{A|N} = \frac{e^{\frac{V_{A|N}}{\Phi}}}{\sum_{A'} e^{\frac{V_{A'|N}}{\Phi}}} \tag{9}$$

Consequently, the probability of an individual choosing lower level alternative A is the product of the above two expressions:

$$P_{NA} = P_N . P_{A|N} \tag{10}$$

In the expressions above φ is a scale parameter and *I* is the logsum term, or inclusive value (IV) term, given by

$$I = \log \sum_{A'} e^{\frac{V_{A'|N}}{\Phi}} \tag{11}$$

The scale parameter, φ, is also referred to as the IV parameter. This is sometimes described as an inverse measurement of correlation amongst alternatives. This is because for the nested logit model to be consistent with the utility maximization theory, the scale parameter must be between 0 and 1. The closer the value of φ is to unity the smaller is the correlation in unobserved characteristics of alternatives within each nest. If the value for φ is 1, the nested logit model is equivalent to a multinomial logit model.

5.2 Models Specifications

In addition to experimenting between the basic MNL and the nested structure two sub models are developed as an extension of the basic MNL model. These sub models explore the effect of interaction terms between weather and the age and weather and gender variables on mode choice. The following paragraphs describe model specifications common to all models and also those specific to individual models.

Several general rules were applied to all model specifications. These include constraints on cost coefficients, defining feasible travel alternatives criteria and selection of reference alternative and the reference category for each categorical variable. The parameters for driving cost, parking cost and transit cost are constrained to be the same. While coefficients for these variables remain significant and negative if such a constraint is not applied, the corresponding values of time of the non-constrained model are less sensible. Moreover, the non-constrained model provides little improvement in the adjusted ρ^2 value and no improvement in prediction success of the model. For a more detailed comparison of the two options please refer to Appendix C. Auto drive is set as the base mode relative to which parameters are estimated for all other modes. It is numerically advantageous to set the mode with highest number of sample points as the base mode. The temperature category of 26 to 30^{o}C is set as the base temperature category. A base category is required since temperature variables are of the dichotomous type. Parameters estimated for all other temperature categories are therefore relative to this category. Similarity, for age variables, the category indicating age 55 to 65 is set as the base age category. Lastly, all walk and bicycle alternatives that resulted in greater than 45 minute trip times were eliminated from the choice set of trip makers at the model estimation stage in order to prevent the estimation from trying to fit the model to outliers. This 45 minute threshold was set based on previous analysis of the TTS data (Coleman 2002).

Two nested structures were evaluated in the modeling process based on general MNL evaluation criteria of goodness-of-fit and parameter significance, in addition to meeting the φ range criteria discussed earlier. Figure 5-2 illustrates these two options. In option A motorized and non-motorized were selected as the two nests at the upper level, while in option B the transit, auto driver and auto passenger modes are treated as degenerate nests while the only two grouped modes are walk and bike.

Option A) **Option B)**

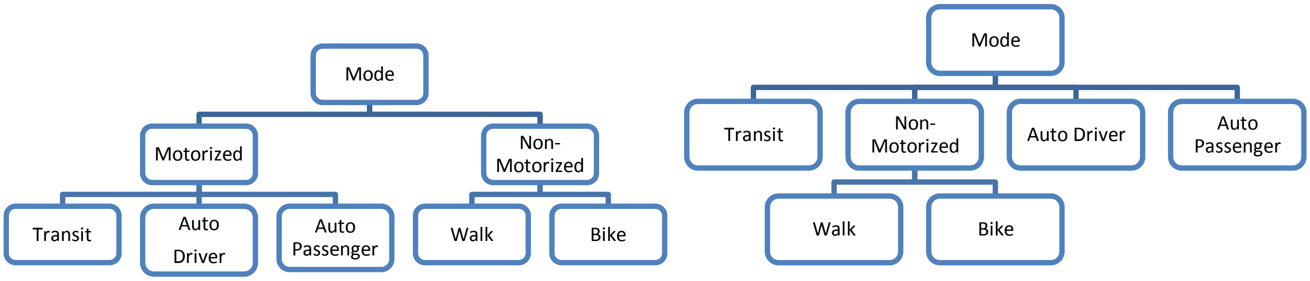

Figure 5-2 Nested logit model structure options A) and B)

Two sub-models, exploring the interaction between weather and gender and weather and age, are also estimated. These will be referred to as the gender interaction model and the age interaction model, respectively. For the age interaction model, nine dummy variables corresponding to nine temperature ranges would have to be interacted with six dummy variables corresponding to six age categories, resulting in 36 categories, with few data points in some. The limited number of data points corresponding to some age and temperature interaction cases ultimately results in insignificant coefficients. To tackle this issue the age and temperature categories were aggregated to some extent. Instead of the original nine temperature categories illustrated in Table 3-5 temperatures are aggregated into four categories. Similarity, the six age categories are aggregated to five categories for this sub-model. For the gender interaction model this does not cause an issue since the nine dummy temperature variables were interacted with only two dummy gender variables, therefore the data still remain quite aggregate.

All parameter estimates were obtained using the commercially available software package Stata IC version 10 which uses Full Information Maximum Likelihood to solve the system of equations described above.

5.3 Nested Logit Modelling Results

After exploring the two nested structure introduced in Figure 5-2 and experimenting with shifting various variables between the upper and lower nests it was concluded that the nested logit approach is not suitable for modelling the impact of weather on mode choice. This is because the Inclusive Value terms for all different variations of the model are not statistically different from one. This implies that there is no correlation in the unobserved characteristics of the grouped modes and that the MNL model can predict mode share with similar success. Ewing et al. (2004) in a study of student mode choice came to a similar conclusions after experimenting with some nested structures for grouping non-motorized modes together. This further supports the idea that there are no correlation amongst the unobserved characteristics of trip makers who walk and bike.

Detailed results of the nested modelling work is provided in Appendix C. Model results presented are for the nesting structure displayed in Figure 5-2-B. The same nesting structure, denoted as “tree structure” by stata is displayed in the stata output format. As the results show, model estimation required 118 iterations. This, compared to the 6 or 7 iterations required for the basic MNL model, suggests that convergence was hard to achieve. The time required for each iteration for nested logit modeling estimation is about 3 minutes, resulting in about 6 hours for estimating the model. The first set of results correspond to coefficients estimated for level of service variables, including travel times and travel costs. Type 2 equations, as denoted in the Stata output, refers to coefficient estimations for variables specified in the upper level of the nesting structure by the modeller. That is the active nest, in addition to the auto passenger, auto driver and transit modes, which appear in the structure as degenerate nests. In the case of degenerate nests it makes no difference whether the modeller specifies certain variables to be estimated at the upper or lower level, since there is only one nesting level. All coefficients are estimated relative to the drive mode, which is why coefficients for the drive mode are denoted as “(base)” in the estimation output.

The mode equation, as denoted in the Stata output, refers to coefficient estimations for variables specified in the lower level of the nesting structure by the modeller. The decision about which variables should be included under which nesting level is a judgment call made by the modeller. In this case the author experimented with a number of options, while keeping in mind the motivation for grouping the walk and bike modes under the active nest. Under the assumption that the two active modes share certain unobserved characteristics, most non-weather related variables are included in the upper level nest. Moreover, assuming that weather conditions have different impacts on the walk and bike mode, these variables are included in the lower level in order to have separate sets of coefficients estimated for each mode.

The final set of estimation outputs for the nested model is the table of dissimilarity parameters. The parameters estimated for the degenerate nests are expectedly 1. As described earlier, a dissimilarity parameter of 1 suggests that there would be no difference in the coefficients estimated if nesting was not applied. Degenerate nests are equivalent to having no nesting, since there are no upper and lower levels specified in their case. The dissimilarity parameter for the active nest is estimated to be 0.98, which is very close to 1, suggesting that the nesting results would be almost equivalent to the basic MNL form of the model.

5.4 Multinomial Logit Modelling Results

Results of the MNL model estimation are presented in Table 5-1. More detailed model results, including the values of standard errors, t-stats, and 90% confidence intervals are provided in Appendix B. Significant parameters, along with their level of significance are presented in the table, while all variables with lower than 90% significance were dropped during the model estimation stage. The adjusted ρ^2 value for this model is 0.23, which is similar to that of some comparable models (McElroy 2009) and according to McFadden (1979) is within the acceptable range of 0.2 and 0.4. Other mode choice models however, developed by Miller et al. (2005) and Roorda et al. (2007), report larger ρ^2 values of above 0.5, indicating better goodness of fit. One reason for the lower than usual ρ^2 value is that only trips where all modes were available for are being modelled here. It is anticipated that prediction would be easier, and result in a higher ρ^2 if all trips were modelled. The ρ^2 value is defined as:

$$\rho^2 = 1 - \left(\frac{L-d}{L_0}\right), \qquad (12)$$

where L is the Log likelihood for the estimated model at convergence, d is the degrees of freedom, and L_0 is the log likelihood of the constant only model.

The log likelihood at convergence is formulated as

$$L = \sum_{t=1}^{N} \sum_{i=0}^{I} d_{ti} \ln p(y_t = i), \tag{13}$$

where

$$d_{ti} = \begin{cases} 1 & \text{If individual } t \text{ chooses alternative } i \\ 0 & \text{Otherwise} \end{cases} .$$

In general the model parameters have the expected signs and magnitudes. The following detailed observations are made:

5.4.1 Level of Service Variables

The relative magnitude and sign of the travel time and cost coefficients are reasonable. Wait time is weighted most negatively, followed by walk time, bike time, auto in-vehicle travel time and transit in-vehicle travel time, in increasing order. The coefficients for auto drive cost, transit cost and parking cost are constrained to be equal. Similarly, the coefficients for walk time and transit walk time are constrained to be the same. The coefficients for walk travel time and bike travel time are almost equal, although they were not constrained to be, suggesting a similar impact of travel time on walking and cycling utilities. The values of time for auto drivers and transit riders, the two modes that have a cost associated with them, are calculated to be $13.0 and $2.5 respectively. It is expected for the transit mode to have a relatively smaller value of time than the auto mode, however both values are lower than those calculated for other models estimated using the TTS data (Miller et al. 2005; Roorda et al. 2009; McElroy 2009). It is anticipated that this is due to the very specific nature of the sample used here, and the fact that there is very little variation in the data for transit fare in Toronto, which follows a flat fare structure.

Table 5-1 Multinomial logit model estimation results

	Variable	Description	Coefficient
Level of Service Variables	aivtt	Auto in-vehicle travel time	-0.057
	tivtt	Transit in-vehicle travel time	-0.011
	ccost	Auto fuel cost	-0.267
	tcost2	Transit travel cost	-0.267
	pkCost	Parking cost	-0.267
	twaitt	Transit wait time	-0.151
	twalkt	Transit walk time	-0.067
	walkt	Walk time	-0.067
	biket	Bike time	-0.067

	Variable	Description	Auto Passenger	Transit	Bike	Walk
Land-Use Variables	Arterial_ Density	Ratio of kilometers of arterial road over all roads (average of origin and destination zones)	0.417*	0.671	-1.31	0.796
	Population_Density	Number of persons per square kilometer		10.684*		45.663
	Intersection _Density	Number of intersections per square km (sum of origin and destination zones)		0.102	0.155	0.128
Socio-Economic Variables	n_person	number of persons in household	0.345	0.185	0.053**	0.076
	n_vehicle	number of vehicles in household	-0.73	-1.006	-0.965	-0.917
	empft	full time employed		-0.675*		
	emppt	part time employed		-0.582*		
	empwahft	full time employed, work at home	-0.314**	-1.726	-0.405**	-1.145
	empwahpt	part time employed work at home		-1.52		
	male	gender (1 if male)	-1.403	-0.781	0.315	-0.541
	agebelow18	above 18 years of age	2.666	1.753		2.011
	age18_24	between 18 and 24 years old	0.922	1.126	1.183	1.029
	age25_39	between 25 and 39 years old		0.264	0.986	0.377
	age40_54	between 40 and 54 years old	-0.27		0.726	
	ageabove65	above 65 years old		-0.346*	-1.009**	-0.525*
Time-of-Day Variables	amp	AM Peak Period	-0.27	-0.504	-0.488	
	pmp	PM peak Period		0.348		0.477
Weather Variables	tempbelow0	temperature below 0 degrees	0.258*		-0.793*	
	temp1_5	temperature between 1 and 5 degrees	0.189		-0.478	-0.203*
	temp6_10	temperature between 6 and 10 degrees	0.104*		-0.54	
	temp11_15	temperature between 11 and 15 degrees			-0.255*	
	temp16_20	temperature between 16 and 20 degrees				
	temp21_25	temperature between 21 and 25 degrees				
	temp31_35	temperature between 31 and 35 degrees				
	tempaabove35	temperature above 35 degrees				
	cloud	Cloudy skies, no precipitation	-0.082*			
	rain	rainy conditions	-0.125*		-0.309*	0.317*
	showers	showers			-0.412**	0.195**
	wind	Wind speed in km/h	-0.002**		-0.006**	-0.003**
	_cons	Constant	-1.727	0.708*	-3.187	-0.171**

Note: Coefficients indicated with no asterisk are significant at 99%, coefficients indicated with one asterisk (*) are significant at 95% and coefficients indicated with two asterisk (**) are significant at 90%. Variables corresponding to all insignificant coefficients were dropped during the model estimation process.

5.4.2 Land use variables

Population density parameters suggest that density intensification improves walking mode-share most strongly, and transit to a lesser extent, while bicycle and auto passenger mode shares are insensitive to population density. This is likely since the bicycle and auto modes have the advantage of higher travel speeds, while the transit and walk modes both include walking for part or all of the trip distance, and density intensification is known to support shorter walk trips in addition to more frequent transit stops. Connectivity of the street network, represented by the intersection density variable, most significantly influences bicycle mode-share followed by walking and transit to lesser extents. Lastly, arterial density, which is a measure of ease of auto travel flow in the neighbourhood, has a negative parameter for the bike mode, while positive for all other modes. This makes sense since, given that most arterial roads in Toronto do not have a bicycle lane, cyclists often prefer to ride on non-arterial roads where there is less vehicle traffic. Arterial roads, however, are where stores and services are mostly located, so they provide better destinations for pedestrian trips, in addition to more busy and secure walking environments, compared to less travelled roads. Moreover, it is likely that the motorized modes are positively affected by more arterial roads since it implies faster travel times.

5.4.3 Socioeconomic Variables

Estimated parameters suggest that living in larger households increased the utility of being auto passengers or transit riders, followed by walk and bike to lesser extents. Additionally, the more vehicles available per household the higher the utility of driving is compared to all other modes. Individuals working full time at home experience a disutility in taking transit, followed by walking, biking and being an auto passenger. Generally, transit is least attractive to individuals working at home, most probably because these individuals do not make regular trips during peak hours, which are the types of trips transit supports best. Male trip-makers experience a disutility when they are auto passengers, take transit or walk, in descending order, but have a positive utility for bike, pointing at the large male to female ratio of cyclists in Toronto. As expected, the utilities of being an auto passenger, taking transit or walking are most strongly and positively affected in younger people and gradually decreases as people get older. This is due to lack of funding for owning or driving a car.

5.4.4 Weather Variables

The parameters for the temperature categories provide some interesting insight into commute mode choice. The estimates suggest that in temperatures higher than 15 ^{o}C the bicycle mode becomes insensitive to temperature, while for temperatures below 15 ^{o}C the utility of cycling gradually decreases. The walk mode is only sensitive to temperatures of 1 to 5 ^{o}C. Moreover, compared to the parameter for walk mode in the 1 to 5 ^{o}C temperature range, the bike mode is affected by cold temperatures twice as much. One can conclude that the walk mode is generally insensitive to temperature, with the exception of temperatures of just above zero, when it is not only cold, but precipitation is in liquid form and is therefore more of a deterrent.

Wind speed negatively affects cycling utility twice as much as walking, which makes intuitive sense since cycling in windy conditions is much more energy intensive and inconvenient than walking. Similarly, precipitation in the form of showers negatively impacts cyclists about twice as much as pedestrians. It is anticipated that this is due to the fact that pedestrians have more and better alternatives for staying dry such as holding an umbrella. Also intuitively, rain negatively impacts cyclist slightly less than shower. For the walk mode however the rain parameter comes out to be positive, suggesting that the utility of walking increases in rainy conditions. One explanation for this is that there may be a slight shift towards walking from the cycling mode in rainy conditions.

The utility of being an auto passenger gradually decrease as temperature increases. However, this mode is not affected by temperatures above 10^{o}C. It is also surprising to see that the transit mode is seemingly insensitive to all temperatures. Another observation that may not be intuitive is that the utility of being an auto passenger decreases in cloudy, rainy and windy conditions. Further explanation on these will be provided later in the discussion of the result of interaction models.

5.5 Results of Interaction Models

In order to gain further insight into the impact of weather variables on mode choice two sub models are also developed using some interaction terms between weather conditions and different demographic groups. The first sub-model looks at the interaction between age groups and weather variables, and the second sub-model explores the interaction between gender and weather variables. Using interaction variables means that there are a smaller number of observations available for parameter estimation for some variables. This has resulted in some interaction terms coming out to be insignificant. However the advantage of estimating these interaction models is that some other interaction terms corresponding to weather conditions that did not come out to be significant for certain modes in the basic MNL model come out to be significant here. In other words differential effects by gender and age may be hidden in the combined model. The following subsections evaluate the estimated parameters by these two models. Coefficients for travel time and costs, in addition to coefficients for all non-weather related variables for these two models are similar to what is presented in Table 5-1 and therefore are not discussed here. Similar adjusted ρ^2 values and prediction success results as those presented later in Table 5-4 are also calculated for the interaction models. The complete set of estimated coefficients, along with standard errors, t-statistics and 90% confidence intervals are provided in Appendix B.

5.5.1 Gender Interaction Model

Results of the gender interaction model are presented in Table 5-2. Several interesting outcomes are apparent when comparing to the basic MNL results.

Even after controlling for general gender effects on mode choice, females' tendency to bike is about 1.5 times more negatively affected by low temperatures than men. Interestingly however, it appears that males' utility of cycling is more drastically affected by change in temperature than females'. Female cyclists appear to be insensitive to wind speed and various sky conditions, while male parameters are similar to those suggested by the basic MNL.

In the basic MNL model presented earlier none of the temperature category variables were identified to be significant for the transit mode, which was puzzling. The interaction model results suggest that there in fact is a significant impact by temperature on transit mode choice. These effects are however very different for male and female trip makers. This explains why, when grouped together, they would be estimated to be insignificant. Increase in temperature results in increased utility of transit for both genders.

Some interesting results are also evident for the sky condition variables for the transit mode, which all came out to be insignificant in the basic MNL model introduced previously. The interaction model results suggest that after controlling for general gender effects on transit mode choice the utility of transit improves for male riders in cloudy and rainy conditions, while female riders are insensitive to all sky conditions. This may suggest that while taking transit may be a more routine mode of commuting for females, males use transit as an occasional alternative mode in adverse conditions. However the same cannot be said about changes in temperature since they are more gradual and happen over longer periods of time. The auto passenger results in the interaction model make more intuitive sense than those suggested by the basic MNL model. Results also suggest that, females' utility for being an auto passenger improves in cold and very hot temperatures.

Lastly, parameters suggest increased utility of walking over auto in precipitation conditions. This is similar to the results of the basic MNL model and makes little intuitive sense aside from potential impact of cyclists switching to walking in sub-optimal weather conditions.

Table 5-2 Gender interaction model estimation results for weather variables only

	AutoPassenger		Transit		Bike		Walk	
	male	female	male	female	male	female	male	female
Gender	-1.338	0	-1.048	0	0.494	0	-0.481	0
below 0		0.398*		-0.333*	-0.994*		0.467*	
temp1_5	0.19*	0.255		-0.178*	-0.49*	-0.546*		-0.282*
temp 6_10	0.096**	0.161*	0.079**	-0.237*	-0.427	-0.583		
temp 11_15		0.053**	0.106*	-0.214*	-0.197**	-0.341*		
temp 16_20			0.16*	-0.191*			0.301*	
temp 21_25	base	base	base	base	base	base	base	base
temp 26_30								
temp 31_35		0.682**						1.712**
temp above 35								
cloud	0.398*		0.057**					0.255*
rain	0.255		0.089**		-0.259**		0.192**	0.572
shower	0.161*				-0.512**		0.268**	
wind	0.053**			0.003*	-0.012*			

$\rho^2 = 0.24$

Notes:

1) The coefficients for the gender variable are presented here to indicate how much of the variation is captured by the gender variable alone and how much explained by the weather variables' interaction with gender
2) Coefficients indicated with no asterisk are significant at 99%, coefficients indicated with one asterisk (*) are significant at 95%, coefficients indicator with two asterisk (**) are significant at 90% and insignificant coefficients are blank.

5.5.1.1 Age Interaction Model

Several parameters of interaction terms between temperature and age categories appear to be insignificant due to very disaggregate data and the resulting small number of observations for many of the age-weather combinations. Nevertheless, results of the age interaction model, presented in Table 5-3, provide some interesting insight into the impact of weather on mode choice behaviour of various age groups.

It is interesting to see that younger trip makers are generally more sensitive to colder temperatures than older individuals for the bike and walk modes. In temperatures below 20^{o}C cyclists below 55 years of age are negatively influenced by temperature. This negative influence is greatest for cyclists below 25 years of age, and gradually improves for older age groups. Similar results are evident for the walk mode for temperatures below 5 ^{o}C although to a smaller extent. While there are not enough data points to make any conclusions about the impact of temperature on walk and bike mode share of the 55 to 65 and above 65 age groups, one can speculate that these age groups are more negatively influenced by low temperatures, similar to the below 25-year age group.

Since observations for male and female trip makers are grouped together again in this interaction model, most temperature and sky condition categories appear to be insignificant to the decision to take transit, while results of the gender interaction model suggests that that is not the case. Nonetheless, in spite of combining males and females, it is interesting to see that for individuals below 25 years of age and between 55 and 65 years of age cold temperatures appear to negatively impact utility of the transit mode. It is anticipated that a similar observation could have been made for the above 65 age category if the sample size for this group was larger. Another interesting observation for the transit mode is that only individuals below 25 years of age are negatively affected by rainy conditions, while other age groups remain insensitive.

As reported earlier, results of the gender interaction model suggested that very warm temperatures increase the utility of being an auto passenger for females. Here results of the age interaction model provide further insight on demographic groups that are affected by very high temperatures. It is evident that trip makers of 65 years or older also experience improved utility of being an auto passenger in hot temperatures, while all other age groups are insensitive to these conditions.

Similar to the results of the basic MNL model and the gender interaction model the counter intuitive relationship between rainy conditions and the tendency to walk is again apparent here. It is worth noting here that Muraleetharan et al. (2005) in their study of influence of winter road conditions on pedestrian route choice in Japan's snowiest metropolis suggest that walking increases in winter time due to the switch from cycling to walking. This may be part of the reason for what is observed in this model as well.

Table 5-3 Age interaction model estimation results for weather variables only

Auto Passenger

		Age				
		below 25	25 to 39	40 to 55	55 to 65	above 65
Temperature	below 5		0.093**	0.226	0.311*	0.72*
	6 to 20					
	21 to 30	base	base	base	base	base
	above 30					1.899*
	wind					
	cloud					
	rain				-0.068**	
	shower					

Transit

		Age				
		below 25	25 to 39	40 to 55	55 to 65	above 65
Temperature	below 5	-0.172**			-0.101**	
	6 to 20					
	21 to 30	base	base	base	base	base
	above 30					
	wind					
	cloud					
	rain	0.308*				
	shower					

Bike

		Age				
		below 25	25 to 39	40 to 55	55 to 65	above 65
Temperature	below 5	-1.092*	-0.557	-0.398*		
	6 to 20	-0.745*	-0.45	-0.276**		
	21 to 30	base	base	base	base	base
	above 30					
	wind		-0.008**			
	cloud				0.162*	
	rain		-0.472*			
	shower		-0.758*			

Walk

		Age				
		below 25	25 to 39	40 to 55	55 to 65	above 65
Temperature	below 5	-0.264**	-0.166**	-0.14**		
	6 to 20					
	21 to 30	base	base	base	base	base
	above 30					
	wind		-0.006**			
	cloud					
	rain		0.234**	0.246**	0.068**	0.261*
	shower			0.281**		

$\rho^2 = 0.22$

Notes:

1) Coefficients indicated with no asterisk are significant at 99%, coefficients indicated with one asterisk (*) are significant at 95%, coefficients indicator with two asterisk (**) are significant at 90% and insignificant coefficients are blank

5.6 Additional Model Results

5.6.1 Prediction Success

As a measure for the model's prediction ability it is possible to assess how well the model reproduces the disaggregate mode choices of individuals. The evaluation involves comparing the predicted mode to the actual or observed mode chosen for each specific trip. By summing all predicted and observed choices and cross tabulating the results a prediction success matrix, also known as a confusion matrix, is generated. The rows in a prediction success table represent the sum of choices that the model predicted and the columns represent the sum of observed chosen alternatives. Therefore, the diagonal entries represent cases in which choices are predicted correctly, while off-diagonal entries represent cases in which the model is "confused", hence the term confusion matrix.

Table 5-4, indicates that 59% of the trips are correctly predicted. The Auto drive mode is most accurately predicted with prediction success rates of 73%. Transit and walk trips are predicted at 44% and 47%, respectively, despite the fact that limited transit level of service information was available outside the AM Peak period.

The table indicates that the auto passenger and bicycle mode are poorly predicted. Auto passenger is mostly mis-predicted as auto drive. This is probably due to the fact that there are very few variables available to understand why one would choose auto passenger over auto drive mode, especially in the case of the sample used in this study, where all trip makers have a driver's licence and access to an automobile. The low ratio of correctly predicted bicycle trips may be associated with the small number of cycling trips available in the TTS and the limited set of explanatory variables. Other mode choice modelling efforts using the TTS data such as research by Roorda et al. (2009) on modelling minor modes of transportation and McElroy (2009) on modelling transit pass ownership indicate similar prediction success results.

It should be noted that the prediction success table is quite symmetrical in its off-diagonal terms. This is a positive point suggesting that, for instance, about the same number of bike trips are mis-predicted as transit trips as the number of transit trips mis-predicted as bike trips.

Table 5-4 Prediction success table for the estimated model

		Observed					
		Transit	**Bike**	**Walk**	**Auto Drive**	**Auto Passenger**	**Total Predicted**
Predicted	**Transit**	4662.6	180.4	298.0	4639.0	823.1	10603
	Bike	180.0	28.0	66.1	298.4	39.5	612
	Walk	172.9	59.5	972.6	744.6	137.3	2087
	Adtuo Drive	4669.4	307.6	652.9	19748.4	1763.8	27142
	Auto Passenger	918.2	36.5	97.5	1711.5	349.3	3113
Total Observed		10603	612	2087	27142	3113	43557
% correctly predicted		**44%**	**5%**	**47%**	**73%**	**11%**	**59%**

5.6.2 Model Validation

As a method of validating the model and ensuring that parameters are not being over fitted the basic MNL model is re-estimated using a random 75% subsample of trips. The ρ^2 and confusion matrix of the resulting estimated model is then compared to those of the original model. Results show that the two models have very similar fits and prediction abilities. The resulting estimated model is then applied to the remaining 25% holdout sample in order to test the model's predictive validity. The confusion matrix of the holdout sample shows similar ratios of correctly and incorrectly predicted alternatives, suggesting that the model has good predictive power for an external sample. Detailed results of this test, along with results of experiments with travel cost constraints, discussed earlier in section 5.2, are provided in Appendix C.

Chapter 6 Trip Generation Analysis

So far the impact of weather on mode choice behaviour is described in this document. In order to gain better insight on the impact of weather on overall travel behaviour it is important to investigate the extent to which weather affects the number of trips made by trip makers.

As described earlier, restrictions were applied to the database of trips used in the mode choice modelling component in order to analyze mode shift observations of only those individuals who are not captive to one or some of the five basic modes. The assumption is that applying such restrictions would ensure that trip makers have other available alternatives modes of transportation to switch to in cases of adverse weather. These restrictions were applied at the trip level rather than the person level. However, for the purposes of analysis of trip rates per person, such restriction would have to be applied at the person level in order to account for those individuals who did not report any trips on the day for which they were interviewed. Absence of any reported trips for the survey day could be due to a variety of reasons, adverse weather being one of them. As a result the data restrictions are slightly modified in order for them to be applicable at the person level only. The data are restricted to:

- Individuals who hold a driver's license;
- Individuals who have at least one car in their household;
- Individuals who are employed part time or full time; and
- Individuals whose household and place of employment is within the boundaries of the City of Toronto.

The 20km trip distance threshold that was used in the case of the mode choice model dataset was not applied in this case. This is because here restrictions are applied at the person level rather than the trip level. One way of applying this trip distance restriction at the person level would have been to limit the database to individuals whose home to work travel distance is less than 20km. This would have involved a GIS exercise of mapping trip origin and destinations to the centroid of the reported origin and destination traffic zones and measuring the Manhattan distance between the two points. It was, however, decided that given that only about 3% of trips made by the restricted individuals are made to destinations more than 20 km away this GIS exercise would prove to be almost redundant and was therefore not performed.

In the analysis of trip rates per person in various weather conditions it is important to take time of day into account. Trip rates vary significantly during a weekday, peaking during the morning and afternoon rush hour. For instance, the trip rate per person at 8 AM of a rainy day could be significantly higher than trip rate at 12 PM of a perfectly sunny day; hence, time of day should be taken into account before comparisons and aggregations are made.

In order to determine trip rates per working person for every hour of the day in different temperature and precipitation conditions the following procedure is followed. The four steps outlined below describe the analysis for the sky conditions of clear/cloud, rain and shower. A similar procedure is followed for the different temperature categories.

- Step 1: The numbers of trips made in clear/cloud, rain and shower conditions during the survey period are determined for every hour of the day;

- Step 2: Given the actual date on which each trip maker's travel activity was collected and the hours of different sky conditions that occurred during that day, the number of trip makers who *could* have potentially made trips in different sky conditions is determined;

- Step 3: The results from Step 1 are divided by the results from Step 2 to determine trips /person for every hour of the day;

- Step 4: The daily trip rate in a hypothetical day of 24 hours of clear/cloud, 24 hours of rain or 24 hours of shower conditions is determined by summing up all 24 hourly trip rates for each condition.

As mentioned above, a similar procedure is followed for the nine temperature categories. One complication that arises in trying to obtain hourly trip rates for the below $0^{o}C$ and 21 and $25^{o}C$ temperature categories is that, given the period over which the survey was conducted, such temperatures simply did not occurred during all hours of the day. Below $0^{o}C$ temperatures, for instance, only occurred overnight and for part of the morning peak period. Therefore, before performing step 4 of the outlined procedure above, hourly trip rates had to be interpolated for those hours of the day where trip rates were missing. This interpolation is done based on distribution of trip rates over the 24 hours of the day for other temperature categories where full day data are available.

Figure 6-1 and Figure 6-2 display the daily commuter trip rate at different temperature categories and sky conditions, respectively. The overall average daily trip rate is 1.7 trips/person. It should be noted that the vertical axis on the two figures are not at the same scale; hence they should be compared with caution.

From Figure 6-1 it is evident that daily commuter trip rates at different temperatures are very close to one another. Trip rate peaks at 1.73 trips/person in the 16 to 20^{o}C temperature category, dropping slightly at the higher and lower temperature categories. Due to insufficient data points at the disaggregate level obtaining daily trip rates for temperatures above 25^{o}C is not possible. As a result, for the analysis explained in the following chapter the value for trip rates in the 20 to 25^{o}C category is used for all temperatures above 20^{o}C.

Figure 6-2 suggests that trip rate in 24 hours of clear/cloudy conditions is just above 1.8 trips/person, dropping down to about 1.4 trips/person in shower conditions and just below 1 trip/person in rainy conditions. It is speculated that rain has a stronger effect than shower since duration of rain events is commonly longer resulting in more dramatic behavioural changes. Results of analysis described in chapter 2 also suggest the same trends.

These graphs should be interpreted with caution. As discussed in the literature review, rather than cancelling trips in bad weather conditions, there is evidence of postponing trips to a later time of the day during adverse weather according to some research. Hence, one could speculate that if, for instance, there were 24 consecutive hours of rain on one day, where shifting trips to another time of the day would not make any different, trip rates would not realistically drop to almost half of that of clear days, as Figure 6-2 suggests. People are expected to still go about their daily lives and make most of their routine trips even if the weather does not improve. In the chapter to follow proper application of these hypothetical daily trip rate values will be explained.

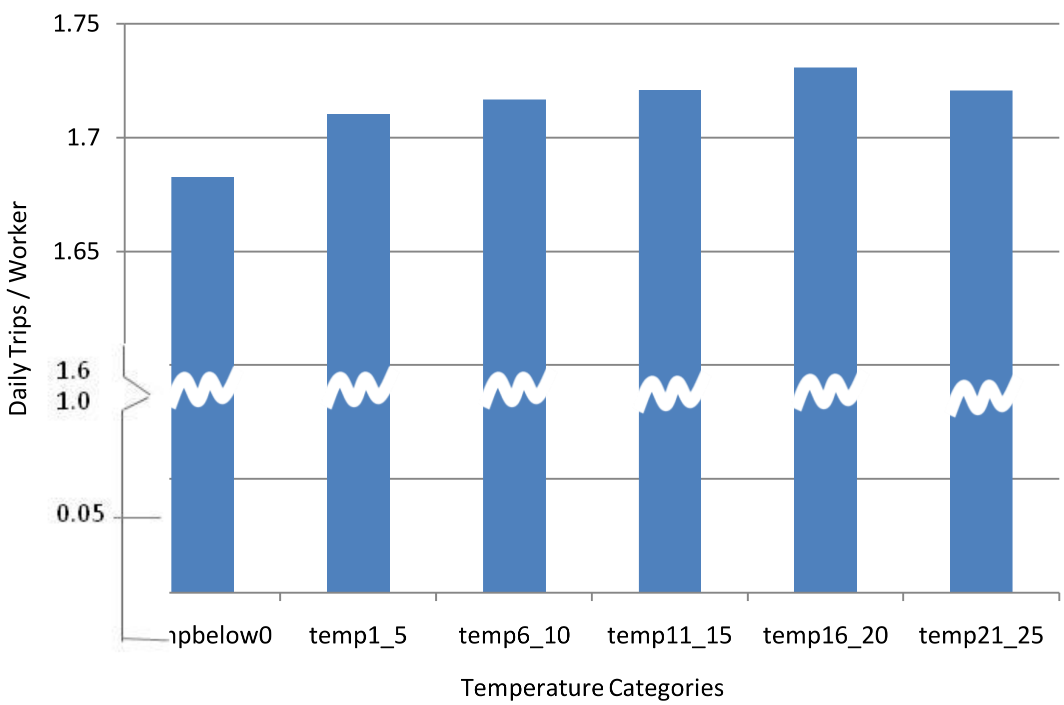

Figure 6-1 Daily trip rate per commuter at different sky conditions

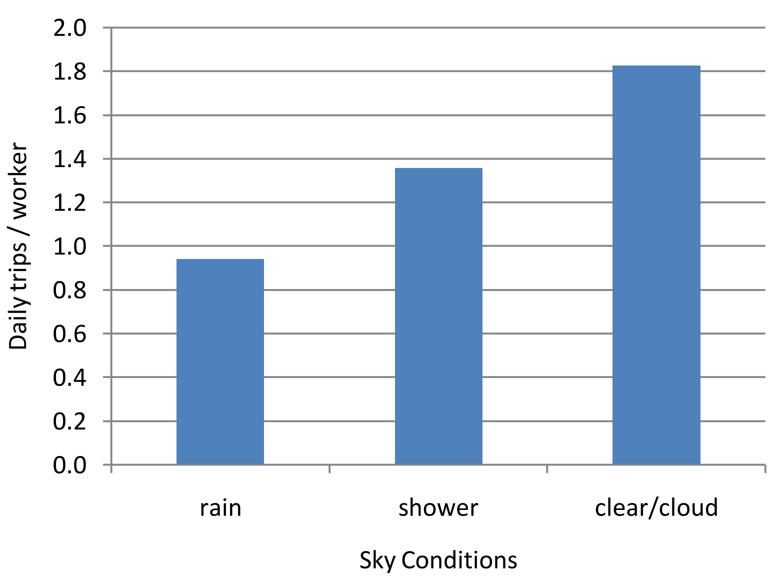

Figure 6-2 Daily trip rate per commuter at different temperature categories

Chapter 7 Climate Change Scenario analysis

So far this report has described the results of the research on the impact of weather on mode choice and trip making. The next step, which is the focus of this chapter, is to combine these two effects so as to assess the overall sensitivity of travel behaviour to weather conditions. Climate change predictions for Toronto for the remainder of this century are used in order to generate several weather scenarios. The expected impact of weather on travel behaviour is then applied to each scenario and the relative changes are assessed.

As with any other prediction exercise there are several factors that are not considered here when applying model results to climate change predictions that are expected to occur in as far as 90 years from now. It is expected that the five basic modes of transportation modelled here may not exist in their current form in the long-term future. Human powered bicycles, for instance, may not be around by the year 2100. Many other factors influencing mode share and trip making such as population and demographics changes are also ignored here. Using climate change predictions is meant to be simply an exercise in assessing the sensitivity of each of the five modes to changes in temperature and precipitation. Additionally, the range of temperature increase and precipitation change predictions for mid and end of the century can also occur as short-term weather changes. Therefore the results of the sensitivity analysis are applicable to short term changes as well.

7.1 Climate Change Predictions for the Toronto Region

The increase in the amount of atmospheric GHGs is expected to have various levels of impact on different parts of the world. An overview of some of the existing climate change prediction models for the Toronto Region reveals ranges of expected temperature and precipitation changes for the current century compared to late 1900 decades. The predictions used in this study are based on the findings of the following national and international reports:

- From Impact to Adaptation: Canada in a Changing Climate (Chiotti & Lavender, 2007),
- Climate Change Projection for Ontario (Science and Information Resources Division, 2007),

- Climate Change 2007: the Physical Science Basis: Contribution of Working group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (Intergovernmental Panel on Climate Change, 2007), and

- Confronting Climate Change in the Great Lakes Region (King, Lindroth, Union of Concerned Scientists & Ecological Society of America, 2003).

Based on the various scenarios assessed by the above studies temperature increases in the range of $1^{o}C$ to $4^{o}C$ for mid-century and $3^{o}C$ to $6^{o}C$ for the end of the century are expected for the study area. In terms of precipitation, all but one of the reports predict an increase in amount of precipitation in the range of 0 to 10% by mid-century and 5 to 20% by the end of the century. The report by Science and Information Resources Division of Ontario (2007) predicts a 10% decrease in precipitation by mid-century and 10 to 20% decrease by the end of the century. The ranges stated above for both temperature and precipitation changes are a general summary of the highest and lowest predictions amongst different scenarios and different reports.

There are of course other ways in which increased atmospheric GHG is expected to impact the study region. However, given the nature of the input data for the mode choice model and trip rate analysis introduced in the earlier chapters, precipitation frequency and temperature are considered to be the two most applicable measures.

7.2 Climate Change Scenario Generation

A total of 10 climate change scenarios are developed based on the results of the above review. These include six temperature increase scenarios and four precipitation change scenarios. In order to reflect the expected temperature increase of 1 to $6^{o}C$ some six separate trip datasets are generated by adding 1 to 6 degrees to the actual temperature at which each trip took place.

Reflecting the predicted change in precipitation amount in the trips database has to be done in a slightly different manner since the changes are in percentage values. The predicted precipitation change is represented as four scenarios including 20% decrease, 10% decrease, 10% increase and 20% increase in the number hours with rain and shower conditions. For the two precipitation increase scenarios, random samples of hours of clear and cloud conditions, equal in number to 10% and 20% of hours with rain and shower conditions, is selected. The sky conditions of trips taking place during these hours are then changed to rain or shower, according to their observed proportions, to reflect the increase.

Similarly, for the precipitation decrease scenarios, random 10% and 20% samples of hours of rain and shower are selected. The sky conditions of trips taking place during these hours are then changed to clear or cloudy, according to their observed proportions, in order to reflect the decrease in precipitation. Each random sampling process is conducted four times and statistical tests are conducted in order to confirm that the resulting changes are statistically significant.

The gender sub-model, which provides the best mode choice estimates, is applied to each of the six temperature increase scenarios and the four precipitation change scenarios in order to measure the impact of temperature and precipitation change on mode choice. For the temperature scenarios dummy variables are regenerated for each temperature category used in the mode choice models based in the new temperature values. It is assumed that all other variables stay constant in all cases. The change in the probabilities of each mode in each scenario compared to the original observed data reflects the impact of the expected weather changes on mode choice.

The process of applying the determined daily trip rates discussed in Chapter 6 to the temperature and precipitation change scenarios is formulated below.

Denotations:

D_i = Data corresponding to scenario i, where $i = \left\{\begin{array}{ll} 1,2,3,4 & \text{for precipitation change scenarios} \\ 5,6,7,8,9,10 & \text{for temperature increase scenarios} \end{array}\right\}$

d_{is} = Number of records in Di that fall under the sky condition s,

where $s = \left\{\begin{array}{ll} 1 & \text{If sky condition is clear/cloud} \\ 2 & \text{If sky condition is rain} \\ 3 & \text{If sky condition is showers} \end{array}\right\}$

d_{it} = Number of records in Di that fall under the temperature category t,

$$\text{where } t = \begin{cases} 1 & \text{if temperature is below } 0^{o}\text{C} \\ 2 & \text{if temperature is between 1 and 5 } ^{o}\text{C} \\ 3 & \text{if temperature is between 6 and 10 } ^{o}\text{C} \\ 4 & \text{if temperature is between 11 and 15 } ^{o}\text{C} \\ 5 & \text{if temperature is between 16 and 20 } ^{o}\text{C} \\ 6 & \text{if temperature is above 20 } ^{o}\text{C} \end{cases}$$

r_s = trip generation rate under sky condition s (from chapter 6).

r_t = trip generation rate under temperature category t (from chapter 6).

R_i , the trip generation rate for scenario i, is calculated by multiplying r_s or r_t by the percentage of trips in each corresponding sky condition, s, or temperature category t. This is to obtain an overall weighted average trip rate to be applied to each scenario. This operation is formulated below.

R_i = Trip generation rate for scenario i = $\sum_{s=1}^{3}\left(\frac{d_{is}}{\sum_{s=1}^{3} d_{is}} \times r_s\right)$ (14)

, for i = {1, 2, 3, 4}, and

R_i = Trip generation rate for scenario i = $\sum_{t=1}^{6}\left(\frac{d_{it}}{\sum_{t=1}^{6} d_{it}} \times r_t\right)$ (15)

, for i = {5, 6, 7, 8,9, 10}.

The weighted average trip generation rates, R_i, is multiplied by the number of trips predicted for each mode for each scenario. This captures the combined effect of mode choice and trip rate on the dataset as a result of the predicted climate change for the Toronto region.

7.3 Model Application Results

Figure 7-1 displays the combined effect of mode choice and trip rate as a result of temperature increase. It is evident that amongst the five modes the bicycle mode is most positively affected by the temperature increase. There is a 17% increase expected in the number of cycling trips for the 6^{o}C temperature increase scenario compared to the base case. At a 2% increase in number of trips the walk and transit modes also display increases, though not to the extent of cycling trips. As expected, the drive mode experiences very little change in trip numbers under different scenarios. The auto passenger mode however, experiences a relatively significant drop of up to 7% under the 6^{o}C temperature increase scenario. Such a result is expected since auto passengers are often flexible and prone to switching to modes such as bicycle, transit and walk with improved weather conditions.

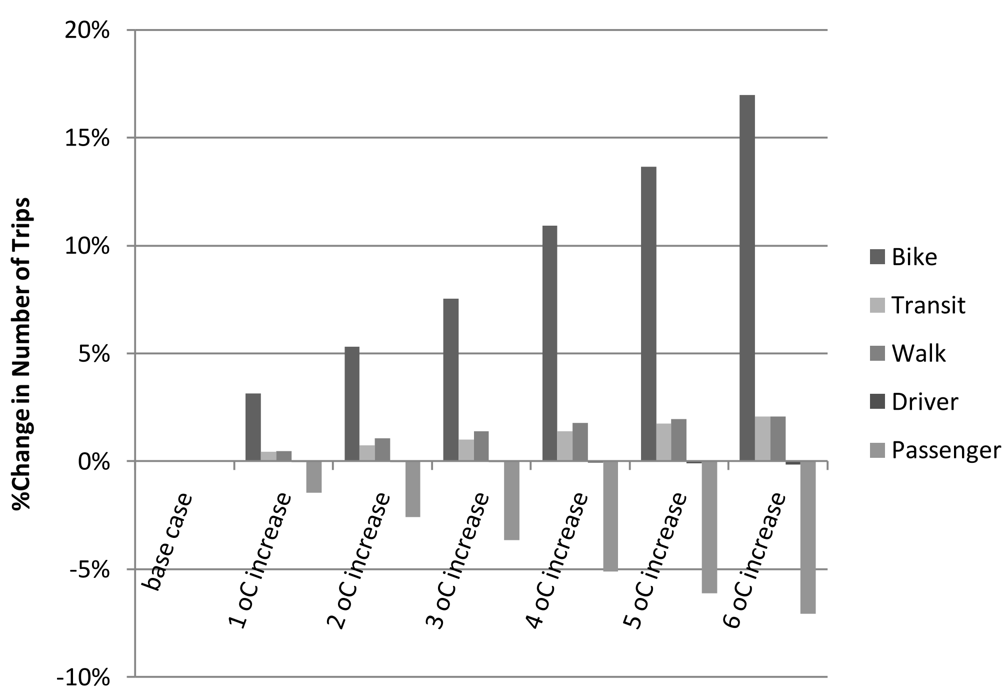

Figure 7-1 Change in number of trips made by each mode under each temperature scenario

Results of the precipitation change scenarios are presented in Figure 7-2 as percentage change of the predicted number of trips compared to the observed (or base) case. The combined mode-share and trip rate results are much less dramatic than those for the temperature scenarios. For the precipitation change scenarios, unlike the temperature increase results, all modes experience an increase in trip numbers under the reduced precipitation scenarios and a decrease in trip numbers under the increased precipitation scenarios. This suggests that the trip rate effects, which apply equally to all modes, are stronger than mode choice effects, which are mode specific. At a 1.6 % increase cycling trips experience the most increase in numbers under the decreased precipitation scenario, compared to other modes. Auto passenger, auto driver and transit trips all increase by about 1.4% under the 20% decrease in precipitation scenario and decrease by 1.5% under the 20% increase in precipitation scenario. Walk trips experience only about 1% increase and decrease under the least and most precipitation change scenarios, respectively. This relatively lower change is due to the somewhat counter intuitive results observed in the mode choice models for the walk mode in rainy conditions, as discussed earlier.

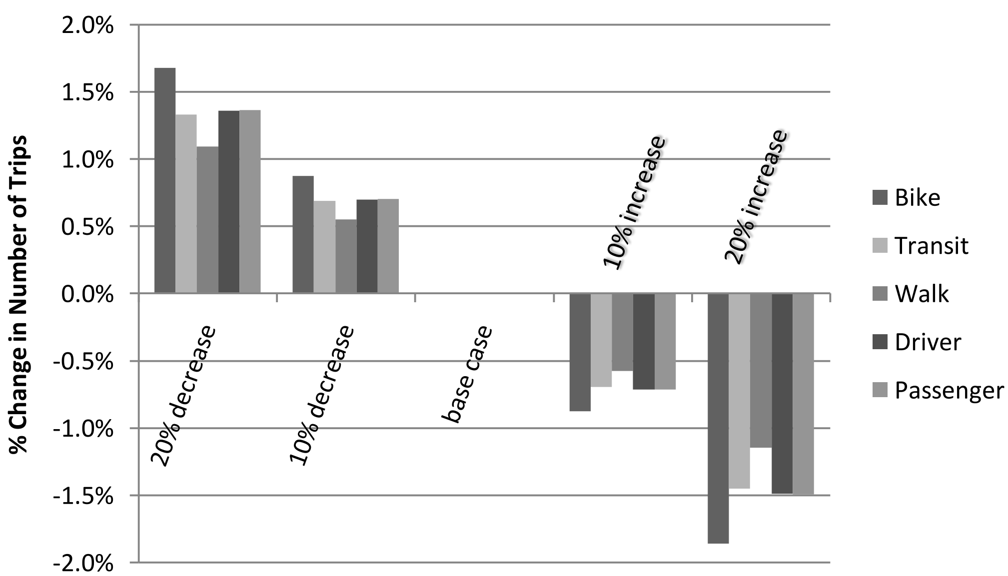

Figure 7-2 Change in number of trips made by each mode under each rain frequency change scenario

Although the changes in number of trips under the temperature increase scenarios are quite large, especially for the bicycle and auto passenger mode, the percentage point changes in mode share

are much smaller. As Figure 7-3 illustrates, there is just over a 0.4 percentage point increase in transit, and 0.2 percentage point increase in cycling expected under the most aggressive temperature increase scenario. Conversely, mode shares for auto passenger and auto driver are expected to drop by just over half a percentage point and just over 0.2 percentage points, respectively, under the 6°C increase scenario. Figure 7-4 suggests even smaller mode share changes for the precipitation change scenarios.

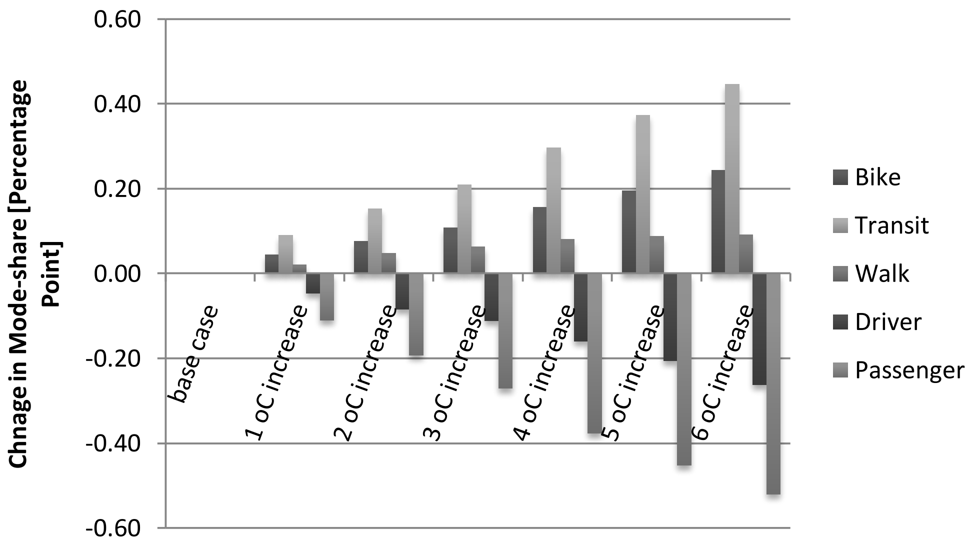

Figure 7-3 Change in mode share under each temperature increase scenario

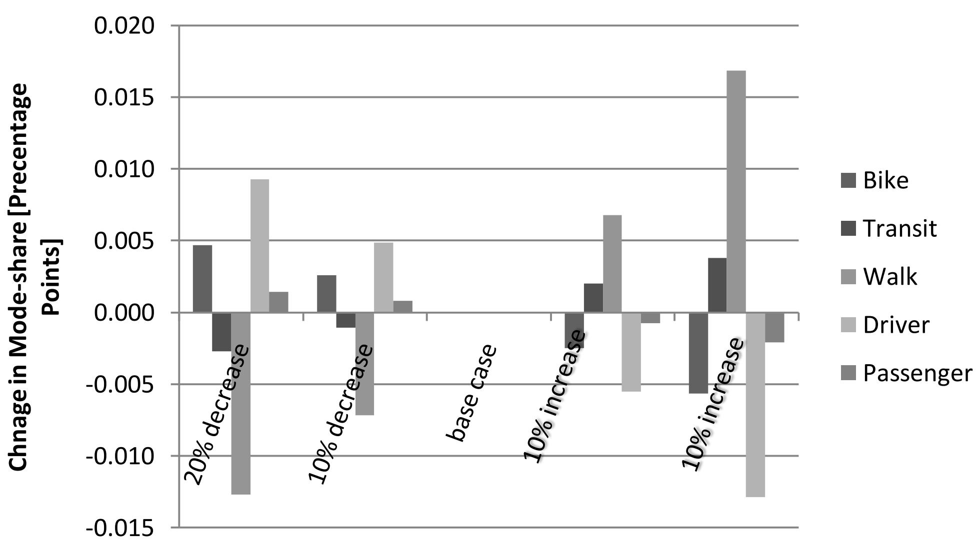

Figure 7-4 Change in mode share under each precipitation change scenario

Chapter 8 Conclusions

8.1 Summary of Major Findings and Conclusions

This thesis explores the impact of weather conditions and climate change on commuter travel activity, with a focus on active modes of transportation. This is achieved by empirical analysis of location-specific bicycle volumes and applying a multinomial logit (MNL) modelling approach to the Transportation Tomorrow Survey data in analysis of daily work trips. In addition to a basic MNL model, two interaction models are also developed in order to explore interaction of demographic groups with weather conditions. Results of these interaction models combined with the commuter trip rate analysis provide further insight into the sensitivity of travel behaviour to expected changes in weather conditions as a result of climate change.

The preliminary analysis of the relationship between weather and bicycle flow rates provides some useful insight. Results show that amongst all sky conditions, rain has the largest negative impact on cycling, while snow has a much smaller impact. It is also evident that adverse sky conditions have small or insignificant impact on leisure cycling while commuter cycling flows are strongly influenced. Lack of information on the demographics of trip makers, and characteristics of other available mode options set limitations on this preliminary data set and the type of analysis that could be performed on it. A multinomial mode choice analysis was therefore developed using a more comprehensive database.

The dataset used for the mode choice analysis is a restricted dataset of home-based work trips made using the five basic modes of auto drive, auto passenger, transit, bike and walk, amounting to 43,557 trips. The data are taken from from the 2001 Transportation Tomorrow Survey of the Toronto region. Since this study aims to analyse behaviour of individuals who are not captive to a limited choice set of travel modes, a series of constraints are applied to the data. These include restricting the sample to individuals who have a driver’s licence, and have access to a vehicle in their household. Furthermore, trips are limited to those that could potentially be made using any of the five modes. Travel data are combined with hourly weather data for the City of Toronto obtained from Environment Canada. Weather features incorporated in the analysis include wind speed, four precipitation conditions and categories of temperature ranges.

In addition to the anticipated impacts of weather condition on walking and cycling modes the mode choice model component of this study offers some interesting insights. Younger individuals' tendency to walk and bike is most negatively affected by cold temperature compared to older age groups. The bicycle mode is sensitive to temperatures only in conditions below 15^{o}C, while walk trips are only sensitive to temperature below 5^{o}C and to a smaller extent than bike trips. Wind speed negatively influences cyclists about twice as much as pedestrians. Similarly, precipitation in the form of showers affects cyclists more than pedestrians. Lastly, females' tendency to bike is about 1.5 times more negatively affected by cold temperatures than men. A puzzling observation is that there is consistently a positive parameter for rainy conditions for the walk mode in all three models.

Results of the mode choice models also offer insight into impact of weather on other travel modes. It appears that even after controlling for general gender effects on transit mode choice, male and female transit riders are very differently affected by cold temperatures. The general conclusion however is that transit becomes less attractive to both genders as temperatures decrease. Males' utility of the transit mode increases in cloudy and rainy conditions, while females are insensitive to all sky conditions. Similarly, in precipitation conditions and high wind speeds being an auto passenger becomes more attractive than driving for male trip makers, while females are insensitive. Very warm temperatures appear to encourage females to switch to being auto passengers from auto drivers. Similarly, trip makers of 65 years or older are likely to become auto passengers in very warm temperatures, while all other age groups are insensitive to these conditions.

An analysis of the daily work trip rate based on the studied sample reveals interesting insight on the impact of temperature and precipitation on trip making. A hypothetical full day of rainy conditions is observed to result in almost half as many trips as a hypothetical full day of clear/cloud conditions. Temperature change has a much more subtle impact on change in daily commuter trip rate. Trip rates drop to 1.78 trips/commuter in sub-zero temperatures and peak at 1.82 trips/commuter in the 16 to 20^{o}C temperature category.

The application of the combined effect of the mode choice and trip rate analysis on several climate change scenarios results in some notable observations. Results suggest that cycling trips can increase in numbers by about 17% due to a 6^{o}C increase in temperature, while the auto passenger mode experiences the most significant drop of about 7% under the same scenario. The precipitation increase and decrease scenarios have a much smaller impact on trip numbers, with a maximum of about 1.6% increase in cycling trips under the 20% decrease in precipitation scenario and 1.7% decrease in cycling trips under the 20% increase in precipitation scenario. Although the change in trip numbers is relatively large, change in percentage mode share as a result of change in temperature or precipitation appear to be quite small. The very small number of cycling trips compared to other trips, for instance, means that cycling trips have to increase by 300% in order for cycling mode share to change by only 3%.

It is evident that the impact of weather on travel behaviour in all modes, and more specifically on active modes of transportation, is significant enough to deserve attention at the research, data collection and planning levels.

The analysis provided in this document provides insight on how mode choice decisions of different genders and age groups are affected by weather conditions, especially for the walk and bike mode. From a policy perspective, these results can help with making active transportation promotional policies and programs more successful by targeting specific demographics. As an example, the results can be useful in implementing a pricing scheme for a future public bike-share program. The results suggest that younger individuals' utility of cycling is most sensitive to colder temperatures. In addition, findings show that the bicycle mode becomes insensitive to temperature above 15^{o}C. Discounting younger subscribers of the bike-share program during the shoulder seasons would help keep them on the road, extend the cycling season, and ensure high bicycle volumes and safe cycling experience for all.

It is evident that all modes of travel are affected to a certain extent by weather. This suggests an area of improvement for future travel surveys collected for Toronto and other regions. It is anticipated that observations may be quite different depending on the season during which travel survey data are collected. This also further impacts the accuracy of forecasting models.

8.2 Limitations and Recommendations for Future Work

As the results of this research suggest, while keeping all other factors constant, temperature and precipitation changes have a large impact on number of pedestrian and bicycle trips. This highlights the importance of accounting for weather when comparing data from count surveys of a specific location collected over multiple days. Research by Thomas et al. (2009) on analysis of bicycle count data in the Netherlands suggest that with better information on the impact of weather on bicycle demand weather correction could be used to standardize flow. A future extension to the research presented here is, therefore, to develop weather correction factors for better comparison of flow data.

Due to data limitations it was not possible to look more closely at the impact of sub zero temperatures and winter conditions on commuter mode choice. Another interesting weather feature could be smog. This could be introduction as a dummy variable for days with smog alerts. While there were numerous smog alerts in 2001 and 2002 they all occurred over the summer period during which trip data was not collected.

Another potential improvement to the dataset used for the mode choice modeling component of the thesis is having data on travel and weather conditions of consecutive days in order to investigate the impact of relative change in weather on travel behaviour. Based on anecdotal evidence, it is hypothesized that relative weather conditions of consecutive days could have a different impact on travel behaviour compared to long term gradual changes. For instance, gradual temperature drops allow cyclists to gradually prepare their gear and clothing for colder temperatures while a sudden temperature drop after a week of warm temperature would probably see a drop in cyclist traffic because some riders may not be ready to deal with cold temperatures. Guo et al. (2007), in a study of impact of weather on transit ridership in Chicago suggest that a 5^{o}C increase in temperature during a cold winter should be treated as relatively warm weather, in spite of the fact that it is still cold in an absolute sense.

It is expected that change in weather has different levels of impact on trips of different purposes. This is part of the reason why this thesis focuses on commute trips only. It is anticipated that shopping trips, for instance, are much more likely to be postponed or cancelled in adverse weather compared to commute trips. Investigating the different levels of impact of weather on travel behaviour for different trip purposes such as work, school, shopping, entertainment, drop-off and pick-up would offer some insightful results. Additionally, when it comes to trips made for shopping and leisure purposes, for instance, location choice, in addition to mode choice, is expected to be influenced by weather. This calls for a joint mode choice and location choice model in order to capture the full affect of weather on travel behaviour.

Inclusion of other variables such as kilometres of available bicycle lanes, elevation change for cycling trips, bicycle ownership levels, physical fitness levels and physical activity habits would potentially have improved the predictability of the model. However, the personal characteristics mentioned were not collected as a part of the TTS, and the physical characteristics measures were not available for reasons discussed earlier.

Another limitation to this study may be the decision to group all public transit modes under one "transit" category. Works of Bento et al. (2005) on transit ridership suggests that weather influences bus and rail transit quite differently. Therefore, separating the two may have resulted in slightly different results.

The mode choice model can be improved through application of a number of more sophisticated modeling approaches. Within household interactions such as ridesharing and vehicle allocation can be captured through an agent-based random utility modeling framework with generic algorithm for parameter estimation, as suggested by Roorda et al. (2007). Additionally, incorporating tours in the model would result in improvements. This is because similar to the auto mode, it is important to incorporate tours when modeling bicycle trips since if a bicycle is used for one part of the tour it must be used in other parts of the tour until it is returned home.

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Appendix A: Detailed Multinomial Logit Modelling Results

Basic MNL Model

Iteration	0:00	log	likelihood	=	-42294.2		
Iteration	1:00	log	likelihood	=	-36239.266	(backed	up)
Iteration	2:00	log	likelihood	=	-34118.7		
Iteration	3:00	log	likelihood	=	-33199.5		
Iteration	4:00	log	likelihood	=	-32675.3		
Iteration	5:00	log	likelihood	=	-32657.4		
Iteration	6:00	log	likelihood	=	-32657.2		
Iteration	7:00	log	likelihood	=	-32657.2		

Adjusted Rho-squared 0.226153
Auto Value of Time $ 12.93
Transit Value of Time $ 2.47

Case variable: link Number of cases = 43557

Alternative variable: Mode Alts per case: min = 2
avg = 3.8
max = 5

Wald chi2(72) = 10664.38
Log likelihood = -32665.747 Prob > chi2 = 0.0000

choice	Coeficient	Standard E	z	P>|z|	[95% Conf. Interval]	
Mode						
aivtt	-0.0574522	0.002515	-22.85	0	-0.06238	-0.05252
tivtt	-0.0109742	0.001736	-6.32	0	-0.01438	-0.00757
ccost	-0.266697	0.006318	-42.21	0	-0.27908	-0.25431
tcost	-0.266697	0.006318	-42.21	0	-0.27908	-0.25431
pkCost	-0.266697	0.006318	-42.21	0	-0.27908	-0.25431
twaitt	-0.1508995	0.007167	-21.06	0	-0.16495	-0.13685
twalkt	-0.0667763	0.002146	-31.12	0	-0.07098	-0.06257
walkt	-0.0667763	0.002146	-31.12	0	-0.07098	-0.06257
biket	-0.0666821	0.003885	-17.17	0	-0.0743	-0.05907
AutoDriver	(base alt	ernative)				

AutoPassen~r	Coeficient	std. Error	z	P>|z|	[95% Conf. Interval]	
n_person	0.345	0.014275	24.17	0	0.317089	0.373046
n_vehicle	-0.730	0.029661	-24.6	0	-0.78785	-0.67158
intdensity	(dropped)					
artdensity	0.417	0.165538	2.52	0.012	0.092492	0.741388
popdensity	(dropped)					
empft	(dropped)					
emppt	(dropped)					
empwahft	-0.314	0.189949	-1.65	0.098	-0.68632	0.058265
empwahpt	(dropped)					
male	-1.403	0.041941	-33.46	0	-1.48563	-1.32122
agebelow18	2.666	0.315978	8.44	0	2.046856	3.285469
age18_24	0.922	0.034031	13.54	0	0.394108	0.527508
age25_39	(dropped)					
age40_54	-0.270	0.010623	-6.35	0	-0.08833	-0.04669
ageabove65	(dropped)					
amp	-0.270	0.042245	-6.39	0	-0.3528	-0.18721
pmp	(dropped)					
tempbelow0	0.258	0.114819	2.24	0.025	0.032598	0.482678
temp1_5	0.189	0.025625	3.69	0	0.044458	0.144907
temp6_10	0.104	0.015347	2.27	0.023	0.004701	0.064859
temp11_15	(dropped)					
temp16_20	(dropped)					
temp21_25	(dropped)					
temp31_35	(dropped)					
tempaabove35	(dropped)					
cloud	-0.082	0.048264	-1.7	0.089	-0.17681	0.012385
rain	-0.125	0.07264	-1.73	0.084	-0.26781	0.016929
showers	(dropped)					
Pearson_wind	-0.002	0.001865	-1.18	0.239	-0.00585	0.00146
_cons	-1.727	0.097052	-17.79	0	-1.91725	-1.53681

Transit	Coeficient	std. Error	z	P>|z|	[95% Conf. Interval]	
n_person	0.185	0.010577	17.52	0	0.164585	0.206045
n_vehicle	-1.006	0.022424	-44.86	0	-1.04977	-0.96187
intdensity	0.102	0.004	25.38	0	0.093692	0.10937
artdensity	0.671	0.125761	5.33	0	0.424403	0.917378
popdensity	10.684	4.423116	2.42	0.016	2.014575	19.35287
empft	-0.675	0.310047	-2.18	0.029	-1.28281	-0.06745
emppt	-0.582	0.312186	-1.86	0.062	-1.19358	0.030168
empwahft	-1.726	0.341349	-5.06	0	-2.39525	-1.05718
empwahpt	-1.520	0.456025	-3.33	0.001	-2.41331	-0.62572
male	-0.781	0.027375	-28.53	0	-0.83459	-0.72728
1 agebelow18	1.753	0.342885	5.11	0	1.081264	2.425348
2 age18_24	1.126	0.026977	20.88	0	0.510348	0.616095
3 age25_39	0.264	0.009344	9.41	0	0.069648	0.106275
4 age40_54	(dropped)					
6 ageabove65	-0.346	0.024848	-2.32	0.02	-0.10637	-0.00897
amp	-0.504	0.0399	-12.64	0	-0.58258	-0.42617
pmp	0.348	0.035256	9.87	0	0.278767	0.416968
1 tempbelow0	(dropped)					
2 temp1_5	(dropped)					
3 temp6_10	(dropped)					
4 temp11_15	(dropped)					
5 temp16_20	(dropped)					
6 temp21_25	(dropped)					
8 temp31_35	(dropped)					
9 tempaabove35	(dropped)					
cloud	(dropped)					
rain	(dropped)					
showers	(dropped)					
Pearson_wind	(dropped)					
_cons	0.708	0.320816	2.21	0.027	0.079381	1.336956

Bike

	Coeficient	std. Error	z	P>|z|	[95% Conf. Interval]	
n_person	0.053	0.034135	1.55	0.121	-0.01403	0.119776
n_vehicle	-0.965	0.080083	-12.05	0	-1.12209	-0.80817
intdensity	0.155	0.010934	14.16	0	0.133387	0.176246
artdensity	-1.310	0.371188	-3.53	0	-2.03708	-0.58205
popdensity	(dropped)					
empft	(dropped)					
emppt	(dropped)					
empwahft	-0.405	0.315021	-1.28	0.199	-1.02206	0.212798
empwahpt	(dropped)					
male	0.315	0.090727	3.47	0.001	0.137357	0.492999
agebelow18	(dropped)					
age18_24	1.183	0.123121	4.8	0	0.349991	0.832616
age25_39	0.986	0.060686	5.42	0	0.209838	0.447722
age40_54	0.726	0.046434	3.91	0	0.09052	0.27254
ageabove65	-1.009	0.122411	-1.37	0.17	-0.40808	0.071758
amp	-0.488	0.090006	-5.42	0	-0.66466	-0.31185
pmp	(dropped)					
tempbelow0	-0.793	0.312225	-2.54	0.011	-1.40533	-0.18143
temp1_5	-0.478	0.064885	-3.69	0	-0.36635	-0.112
temp6_10	-0.540	0.039893	-4.51	0	-0.25818	-0.1018
temp11_15	-0.255	0.02975	-2.15	0.032	-0.12218	-0.00556
temp16_20	(dropped)					
temp21_25	(dropped)					
temp31_35	(dropped)					
tempaabove35	(dropped)					
cloud	(dropped)					
rain	-0.309	0.160756	-1.92	0.055	-0.62402	0.006134
showers	-0.412	0.254149	-1.62	0.105	-0.90989	0.08635
Pearson_wind	-0.006	0.004289	-1.39	0.165	-0.01436	0.002447
_cons	-3.187	0.292715	-10.89	0	-3.76117	-2.61375

Walk

		Coeficient	std. Error	z	P>|z|	[95% Conf. Interval]	
	n_person	0.076	0.023349	3.27	0.001	0.030483	0.122009
	n_vehicle	-0.917	0.050712	-18.08	0	-1.01649	-0.8177
	intdensity	0.128	0.008323	15.43	0	0.112084	0.144711
	artdensity	0.796	0.248003	3.21	0.001	0.310336	1.28249
	popdensity	45.663	8.899277	5.13	0	28.22079	63.10532
	empft	(dropped)					
	emppt	(dropped)					
	empwahft	-1.145	0.278494	-4.11	0	-1.69052	-0.59884
	empwahpt	(dropped)					
	male	-0.541	0.060261	-8.97	0	-0.65881	-0.42259
1	agebelow18	2.011	0.395576	5.08	0	1.236008	2.786637
2	age18_24	1.029	0.054315	9.47	0	0.407939	0.620851
3	age25_39	0.377	0.021418	5.87	0	0.083733	0.16769
4	age40_54	(dropped)					
6	ageabove65	-0.525	0.049124	-1.78	0.075	-0.18383	0.008737
	amp	(dropped)					
	pmp	0.477	0.066146	7.21	0	0.347466	0.606755
1	tempbelow0	(dropped)					
2	temp1_5	-0.203	0.037141	-2.73	0.006	-0.17409	-0.0285
3	temp6_10	(dropped)					
4	temp11_15	(dropped)					
5	temp16_20	(dropped)					
6	temp21_25	(dropped)					
8	temp31_35	(dropped)					
9	tempaabove35	(dropped)					
	cloud	(dropped)					
	rain	0.317	0.116972	2.71	0.007	0.08768	0.546201
	showers	0.195	0.159497	1.22	0.222	-0.11785	0.507368
	Pearson_wind	-0.003	0.00289	-1.14	0.256	-0.00895	0.002381
	_cons	-0.171	0.170935	-1	0.317	-0.50618	0.163874

Gender Interaction Model

Iteration	0:00	log	likelihood	=	-42066.3
Iteration	1:00	log	likelihood	=	-35452.1
Iteration	2:00	log	likelihood	=	-33728.8
Iteration	3:00	log	likelihood	=	-32816.2
Iteration	4:00	log	likelihood	=	-32645.1
Iteration	5:00	log	likelihood	=	-32642
Iteration	6:00	log	likelihood	=	-32642

Alternative-specific conditional logit   Number of obs = 167298
Case variable: link   Number of cases = 43557

Alternative variable: Mode   Alts per case: min = 2
avg = 3.8
max = 5

Wald chi2(90) = 10698.74
Log likelihood = -32641.978   Prob > chi2 = 0.0000

choice	Coeficient	Standard E	z	P>|z|	[95% Conf. Interval]	
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Mode						
aivtt	-0.058	0.002516	-22.91	0	-0.06258	-0.05271
tivtt	-0.011	0.001737	-6.33	0	-0.0144	-0.0076
ccost	-0.266	0.006315	-42.18	0	-0.27875	-0.254
tcost2	-0.266	0.006315	-42.18	0	-0.27875	-0.254
pkCost	-0.266	0.006315	-42.18	0	-0.27875	-0.254
twaitt	-0.151	0.007173	-21.1	0	-0.16543	-0.13731
twalkt	-0.067	0.002149	-31.21	0	-0.07129	-0.06287
walkt	-0.067	0.002149	-31.21	0	-0.07129	-0.06287
biket	-0.067	0.003886	-17.19	0	-0.07443	-0.0592
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AutoDriver	(base al	ternative)				
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Auto Passenger

	Coeficient	std. Error	z	P>|z|	[95% Conf. Interval]	
n_person	0.345	0.014248	24.2	0	0.316818	0.372669
n_vehicle	-0.724	0.0296	-24.47	0	-0.7823	-0.66627
intdensity	(dropped)					
artdensity	0.410	0.165362	2.48	0.013	0.085564	0.733772
popdensity	(dropped)					
empft	(dropped)					
emppt	(dropped)					
empwahft	-0.325	0.190022	-1.71	0.087	-0.69734	0.047533
empwahpt	(dropped)					
male	-1.338	0.079286	-16.87	0	-1.49331	-1.18251
agebelow18	2.661	0.315707	8.43	0	2.042594	3.280142
age18_24	0.922	0.034025	13.55	0	0.39452	0.527896
age25_39	(dropped)					
age40_54	-0.268	0.010622	-6.3	0	-0.08774	-0.0461
ageabove65	(dropped)					
amp	-0.253	0.041627	-6.08	0	-0.33459	-0.17141
pmp	(dropped)					
male_tempb~0	(dropped)					
male_temp1_5	0.190	0.084748	2.25	0.025	0.02438	0.356585
male_temp~10	0.096	0.077673	1.23	0.217	-0.05639	0.248081
male_temp~15	(dropped)					
male_temp~20	(dropped)					
male_temp~30	(dropped)					
male_temp3~5	(dropped)					
male_tempa~5	(dropped)					
female_te~w0	0.398	0.149044	2.67	0.008	0.106378	0.690618
female_te~_5	0.255	0.07937	3.21	0.001	0.099356	0.41048
female_te~10	0.161	0.074059	2.17	0.03	0.015673	0.30598
female_te~15	0.053	0.078889	0.67	0.501	-0.10158	0.20766
female_te~20	(dropped)					
female_te~30	(dropped)					
female_t~_35	0.682	0.513619	1.33	0.184	-0.32455	1.688805
female_t~e35	(dropped)					
female_cloud	(dropped)					
female_rain	(dropped)					
female_sho~s	(dropped)					
female_wind	(dropped)					
male_cloud	(dropped)					
male_rain	(dropped)					
male_showers	(dropped)					
male_wind	(dropped)					
_cons	-1.919	0.09483	-20.24	0	-2.10531	-1.73359

Transit

	Coeficient	std. Error	z	P>|z|	[95% Conf. Interval]	
n_person	0.185	0.010518	17.56	0	0.164106	0.205334
n_vehicle	-1.002	0.022395	-44.74	0	-1.04585	-0.95806
intdensity	0.102	0.004	25.47	0	0.094019	0.109697
artdensity	0.669	0.125788	5.32	0	0.42215	0.915232
popdensity	10.853	4.424951	2.45	0.014	2.180748	19.52624
empft	-0.673	0.310165	-2.17	0.03	-1.28053	-0.06471
emppt	-0.585	0.312303	-1.87	0.061	-1.19707	0.027131
empwahft	-1.729	0.341467	-5.06	0	-2.39836	-1.05983
empwahpt	-1.529	0.455804	-3.35	0.001	-2.42219	-0.63547
male	-1.048	0.103047	-10.17	0	-1.25024	-0.8463
agebelow18	1.767	0.34245	5.16	0	1.095497	2.437878
age18_24	1.128	0.02699	20.9	0	0.511282	0.61708
age25_39	0.264	0.009348	9.43	0	0.069794	0.106437
age40_54	(dropped)					
ageabove65	-0.343	0.024856	-2.3	0.021	-0.10596	-0.00853
amp	-0.488	0.040202	-12.13	0	-0.56643	-0.40884
pmp	0.337	0.035398	9.52	0	0.267478	0.406236
male_tempb~0	(dropped)					
male_temp1_5	(dropped)					
male_temp~10	0.079	0.049249	1.61	0.108	-0.01731	0.17574
male_temp~15	0.106	0.051683	2.05	0.04	0.004826	0.207419
male_temp~20	0.160	0.060822	2.62	0.009	0.040373	0.278791
male_temp~30	(dropped)					
male_temp3~5	(dropped)					
male_tempa~5	(dropped)					
female_te~w0	-0.333	0.153128	-2.17	0.03	-0.63301	-0.03276
female_te~_5	-0.178	0.095363	-1.86	0.063	-0.36454	0.009278
female_te~10	-0.237	0.091955	-2.58	0.01	-0.41772	-0.05727
female_te~15	-0.214	0.093058	-2.3	0.021	-0.39681	-0.03203
female_te~20	-0.191	0.096637	-1.98	0.048	-0.38076	-0.00195
female_te~30	(dropped)					
female_t~_35	(dropped)					
female_t~e35	(dropped)					
female_cloud	(dropped)					
female_rain	(dropped)					
female_sho~s	(dropped)					
female_wind	0.003	0.001706	1.77	0.077	-0.00032	0.006363
male_cloud	0.057	0.040949	1.39	0.165	-0.02347	0.13705
male_rain	0.089	0.066863	1.33	0.182	-0.04191	0.22019
male_showers	(dropped)					
male_wind	(dropped)					
_cons	0.843	0.33381	2.53	0.012	0.18894	1.49745

Bike

	Coeficient	Standard E	z	P>|z|	[95% Conf.	Interval]
n_person	(dropped)					
n_vehicle	-0.930	0.076534	-12.15	0	-1.0799	-0.77989
intdensity	0.153	0.010891	14.08	0	0.131957	0.17465
artdensity	-1.338	0.370438	-3.61	0	-2.06409	-0.612
popdensity	(dropped)					
empft	(dropped)					
emppt	(dropped)					
empwahft	-0.433	0.314953	-1.37	0.169	-1.05024	0.184357
empwahpt	(dropped)					
male	0.494	0.195163	2.53	0.011	0.111627	0.876654
agebelow18	(dropped)					
age18_24	1.227	0.12237	5.01	0	0.373673	0.853355
age25_39	1.007	0.060586	5.54	0	0.216894	0.454385
age40_54	0.766	0.046113	4.16	0	0.101241	0.281999
ageabove65	-1.002	0.122325	-1.36	0.172	-0.40669	0.07282
amp	-0.496	0.089058	-5.57	0	-0.67074	-0.32164
pmp	(dropped)					
male_tempb~0	-0.994	0.405415	-2.45	0.014	-1.78849	-0.19929
male_temp1_5	-0.490	0.155148	-2.75	0.006	-0.73113	-0.12296
male_temp~10	-0.427	0.143309	-3.42	0.001	-0.77066	-0.2089
male_temp~15	-0.197	0.144332	-1.37	0.172	-0.48	0.085768
male_temp~20	(dropped)					
male_temp~30	(dropped)					
male_temp3~5	(dropped)					
male_tempa~5	(dropped)					
female_te~w0	(dropped)					
female_te~_5	-0.546	0.21929	-2.49	0.013	-0.97563	-0.11603
female_te~10	-0.583	0.199646	-2.92	0.003	-0.97475	-0.19215
female_te~15	-0.341	0.202181	-1.69	0.092	-0.73737	0.055159
female_te~20	(dropped)					
female_te~30	(dropped)					
female_t~_35	(dropped)					
female_t~e35	(dropped)					
female_cloud	(dropped)					
female_rain	(dropped)					
female_sho~s	(dropped)					
female_wind	(dropped)					
male_cloud	(dropped)					
male_rain	-0.259	0.191981	-1.35	0.177	-0.63567	0.116886
male_showers	-0.512	0.329763	-1.55	0.121	-1.15798	0.134665
male_wind	-0.012	0.005255	-2.27	0.023	-0.02225	-0.00165
_cons	-3.229	0.285084	-11.33	0	-3.78815	-2.67065

Walk

	Coeficient	Standard E	z	P>|z|	[95% Conf.	Interval]
n_person	0.073	0.023313	3.15	0.002	0.027752	0.119139
n_vehicle	-0.919	0.050791	-18.1	0	-1.01871	-0.81961
intdensity	0.129	0.008324	15.47	0	0.112495	0.145124
artdensity	0.797	0.248321	3.21	0.001	0.309805	1.283206
popdensity	45.551	8.909196	5.11	0	28.08941	63.01282
empft	(dropped)					
emppt	(dropped)					
empwahft	-1.132	0.278031	-4.07	0	-1.67705	-0.58719
empwahpt	(dropped)					
male	-0.481	0.094842	-5.07	0	-0.66665	-0.29488
agebelow18	2.007	0.39653	5.06	0	1.229645	2.784014
age18_24	1.026	0.054524	9.41	0	0.406136	0.619865
age25_39	0.380	0.021433	5.91	0	0.084648	0.168663
age40_54	(dropped)					
ageabove65	-0.536	0.049499	-1.8	0.071	-0.18627	0.007762
amp	(dropped)					
pmp	0.477	0.065326	7.3	0	0.348742	0.604816
male_tempb~0	0.467	0.246832	1.89	0.058	-0.01659	0.950971
male_temp1_5	(dropped)					
male_temp~10	(dropped)					
male_temp~15	(dropped)					
male_temp~20	0.301	0.119842	2.51	0.012	0.066069	0.535842
male_temp~30	(dropped)					
male_temp3~5	(dropped)					
male_tempa~5	(dropped)					
female_te~w0	(dropped)					
female_te~_5	-0.282	0.103034	-2.73	0.006	-0.48366	-0.07978
female_te~10	(dropped)					
female_te~15	(dropped)					
female_te~20	(dropped)					
female_te~30	(dropped)					
female_t~_35	1.712	1.065313	1.61	0.108	-0.37568	3.800274
female_t~e35	(dropped)					
female_cloud	0.255	0.092515	2.75	0.006	0.073179	0.435829
female_rain	0.572	0.148553	3.85	0	0.280453	0.862769
female_sho~s	(dropped)					
female_wind	(dropped)					
male_cloud	(dropped)					
male_rain	0.192	0.142274	1.35	0.178	-0.08732	0.470385
male_showers	0.268	0.202582	1.32	0.186	-0.1294	0.664709
male_wind	(dropped)					
_cons	-0.335	0.163021	-2.06	0.04	-0.65459	-0.01556

Age Interaction Model

Iteration	0:00	log	likelihood	=	-42820.5	
Iteration	1:00	log	likelihood	=	-35989.2	(backed up)
Iteration	2:00	log	likelihood	=	-33170.2	
Iteration	3:00	log	likelihood	=	-32671.5	
Iteration	4:00	log	likelihood	=	-32658.4	
Iteration	5:00	log	likelihood	=	-32658.4	
Iteration	6:00	log	likelihood	=	-32658.4	

Alternative-specific conditional logit Number of obs = 167298
Case variable: link Number of cases = 43557

Alternative variable: Mode Alts per case: min = 2
avg = 3.8
max = 5

Wald chi2(83) = 10677.19
Log likelihood = -32658.398 Prob > chi2 = 0.0000

Adjusted Rho-squared	0.235356
Auto Value of Time	$ 12.92
Transit Value of Time	$ 2.46

choice	**Coeficient**	**std. Error**	**z**	**P>|z|**	**[95% Conf. Interval]**	
------------	-----------	------------	---------	--------	--------------	----------
Mode						
aivtt	-0.0573927	0.002515	-22.82	0	-0.06232	-0.05246
tivtt	-0.0109284	0.001736	-6.29	0	-0.01433	-0.00753
ccost	-0.2665295	0.006318	-42.19	0	-0.27891	-0.25415
tcost2	-0.2665295	0.006318	-42.19	0	-0.27891	-0.25415
pkCost	-0.2665295	0.006318	-42.19	0	-0.27891	-0.25415
twaitt	-0.151083	0.00717	-21.07	0	-0.16514	-0.13703
twalkt	-0.0666146	0.002146	-31.04	0	-0.07082	-0.06241
walkt	-0.0666146	0.002146	-31.04	0	-0.07082	-0.06241
biket	-0.0665177	0.003885	-17.12	0	-0.07413	-0.0589
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AutoDriver	(base al	ternative)				

AutoPassen~r						
	Coeficient	**std. Error**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
n_person	0.348009	0.01432	24.3	0	0.319942	0.376076
n_vehicle	-0.7252013	0.029656	-24.45	0	-0.78333	-0.66708
intdensity	(dropped)					
artdensity	0.419869	0.165472	2.54	0.011	0.09555	0.744188
popdensity	(dropped)					
empft	(dropped)					
emppt	(dropped)					
empwahft	-0.3121232	0.189798	-1.64	0.1	-0.68412	0.059874
empwahpt	(dropped)					
agebelow18	2.713308	0.315796	8.59	0	2.094359	3.332257
age18_24	0.4790231	0.035231	13.6	0	0.409973	0.548074
age25_39	(dropped)					
age40_54	-0.071104	0.012634	-5.63	0	-0.09587	-0.04634
ageabove65	(dropped)					
amp	-0.243245	0.041367	-5.88	0	-0.32432	-0.16217
pmp	(dropped)					
male	-1.403223	0.041976	-33.43	0	-1.4855	-1.32095
_lageXte~1_1	(dropped)					
_lageXte~1_3	(dropped)					
_lageXte~1_7	(dropped)					
_lageXte~3_1	0.0932345	0.066248	1.41	0.159	-0.03661	0.223078
_lageXte~3_3	(dropped)					
_lageXte~3_7	(dropped)					
_lageXte~4_1	0.2264148	0.071397	3.17	0.002	0.086479	0.366351
_lageXte~4_3	(dropped)					
_lageXte~4_7	(dropped)					
_lageXte~5_1	0.3113395	0.115847	2.69	0.007	0.084284	0.538395
_lageXte~5_3	(dropped)					
_lageXte~5_7	(dropped)					
_lageXte~6_1	0.7199126	0.361734	1.99	0.047	0.010927	1.428898
_lageXte~6_3	(dropped)					
_lageXte~6_7	1.899382	0.874261	2.17	0.03	0.185863	3.612901
ageXCloud_1	(dropped)					
ageXCloud_3	(dropped)					
ageXCloud_4	(dropped)					
ageXCloud_5	(dropped)					
ageXCloud_6	(dropped)					
ageXRain_1	(dropped)					
ageXRain_3	(dropped)					
ageXRain_4	(dropped)					
ageXRain_5	-0.0683877	0.041327	-1.65	0.098	-0.14939	0.012611
ageXRain_6	(dropped)					
ageXShower_1	(dropped)					
ageXShower_3	(dropped)					
ageXShower_4	(dropped)					
ageXShower_5	(dropped)					
ageXShower_6	(dropped)					
ageXWind_1	(dropped)					
ageXWind_3	(dropped)					
ageXWind_4	(dropped)					
ageXWind_5	(dropped)					
ageXWind_6	(dropped)					
_cons	-1.839559	0.080678	-22.8	0	-1.99768	-1.68143

Transit						
	Coeficient	**std. Error**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
n_person	0.185412	0.010594	17.5	0	0.164649	0.206175
n_vehicle	-1.00431	0.022423	-44.79	0	-1.04826	-0.96036
intdensity	0.10161	0.003998	25.42	0	0.093774	0.109446
artdensity	0.67046	0.125748	5.33	0	0.423999	0.916921
popdensity	10.61452	4.423676	2.4	0.016	1.944275	19.28477
empft	-0.68506	0.311356	-2.2	0.028	-1.29531	-0.07482
emppt	-0.59172	0.313514	-1.89	0.059	-1.2062	0.022755
empwahft	-1.73872	0.342538	-5.08	0	-2.41008	-1.06736
empwahpt	-1.52403	0.456517	-3.34	0.001	-2.41879	-0.62928
agebelow1	1.594263	0.351289	4.54	0	0.905748	2.282777
age18_24	0.494926	0.045686	10.83	0	0.405383	0.58447
age25_39	0.085871	0.009483	9.06	0	0.067285	0.104456
age40_54	(dropped)					
ageabove6	-0.05382	0.024885	-2.16	0.031	-0.10259	-0.00505
amp	-0.49869	0.039909	-12.5	0	-0.57691	-0.42047
pmp	0.343354	0.035259	9.74	0	0.274248	0.41246
male	-0.77902	0.027383	-28.45	0	-0.83269	-0.72535
_lageXte~1	-0.17238	0.1109	-1.55	0.12	-0.38974	0.044982
_lageXte~1	(dropped)					
_lageXte~1	(dropped)					
_lageXte~3	(dropped)					
_lageXte~3	(dropped)					
_lageXte~3	(dropped)					
_lageXte~4	(dropped)					
_lageXte~4	(dropped)					
_lageXte~4	(dropped)					
_lageXte~5	-0.10079	0.090341	-1.12	0.265	-0.27786	0.076275
_lageXte~5	(dropped)					
_lageXte~5	(dropped)					
_lageXte~6	(dropped)					
_lageXte~6	(dropped)					
_lageXte~6	(dropped)					
ageXCloud	(dropped)					
ageXCloud	(dropped)					
ageXCloud	(dropped)					
ageXCloud	(dropped)					
ageXCloud	(dropped)					
ageXRain_	0.308485	0.146593	2.1	0.035	0.021167	0.595802
ageXRain_	(dropped)					
ageXRain_	(dropped)					
ageXRain_	(dropped)					
ageXRain_	(dropped)					
ageXShow	(dropped)					
ageXShow	(dropped)					
ageXShow	(dropped)					
ageXShow	(dropped)					
ageXShow	(dropped)					
ageXWind_	(dropped)					
ageXWind_	(dropped)					
ageXWind_	(dropped)					
ageXWind_	(dropped)					
ageXWind_	(dropped)					
_cons	0.710493	0.322055	2.21	0.027	0.079276	1.341709

Bike

	Coeficient	std. Error	z	P>|z|	[95% Conf.	Interval]
n_person	0.0544107	0.034135	1.59	0.111	-0.01249	0.121314
n_vehicle	-0.965694	0.080138	-12.05	0	-1.12276	-0.80863
intdensity	0.1553402	0.010926	14.22	0	0.133925	0.176755
artdensity	-1.310626	0.371027	-3.53	0	-2.03783	-0.58343
popdensity	(dropped)					
empft	(dropped)					
emppt	(dropped)					
empwahft	-0.4070716	0.314845	-1.29	0.196	-1.02416	0.210013
empwahpt	(dropped)					
agebelow18	(dropped)					
age18_24	1.175655	0.208126	5.65	0	0.767735	1.583575
age25_39	0.6997429	0.110155	6.35	0	0.483843	0.915643
age40_54	0.3798736	0.080976	4.69	0	0.221165	0.538583
ageabove65	(dropped)					
amp	-0.4792867	0.089242	-5.37	0	-0.6542	-0.30438
pmp	(dropped)					
male	0.3139703	0.090715	3.46	0.001	0.136173	0.491768
_IageXte~1_1	-1.091718	0.54212	-2.01	0.044	-2.15425	-0.02918
_IageXte~1_3	-0.7447548	0.378562	-1.97	0.049	-1.48672	-0.00279
_IageXte~1_7	(dropped)					
_IageXte~3_1	-0.5566009	0.171951	-3.24	0.001	-0.89362	-0.21958
_IageXte~3_3	-0.4497177	0.142739	-3.15	0.002	-0.72948	-0.16996
_IageXte~3_7	(dropped)					
_IageXte~4_1	-0.3984188	0.205085	-1.94	0.052	-0.80038	0.003541
_IageXte~4_3	-0.275858	0.167174	-1.65	0.099	-0.60351	0.051798
_IageXte~4_7	(dropped)					
_IageXte~5_1	(dropped)					
_IageXte~5_3	(dropped)					
_IageXte~5_7	(dropped)					
_IageXte~6_1	(dropped)					
_IageXte~6_3	(dropped)					
_IageXte~6_7	(dropped)					
ageXCloud_1	(dropped)					
ageXCloud_3	(dropped)					
ageXCloud_4	(dropped)					
ageXCloud_5	0.1623493	0.070986	2.29	0.022	0.023219	0.30148
ageXCloud_6	(dropped)					
ageXRain_1	(dropped)					
ageXRain_3	-0.4720259	0.243452	-1.94	0.053	-0.94918	0.00513
ageXRain_4	(dropped)					
ageXRain_5	(dropped)					
ageXRain_6	(dropped)					
ageXShower_1	(dropped)					
ageXShower_3	-0.757822	0.419949	-1.8	0.071	-1.58091	0.065262
ageXShower_4	(dropped)					
ageXShower_5	(dropped)					
ageXShower_6	(dropped)					
ageXWind_1	(dropped)					
ageXWind_3	-0.0083177	0.00607	-1.37	0.171	-0.02022	0.00358
ageXWind_4	(dropped)					
ageXWind_5	(dropped)					
ageXWind_6	(dropped)					
_cons	-4.260562	0.357895	-11.9	0	-4.96202	-3.5591

Walk

	Coeficient	std. Error	z	P>|z|	[95% Conf.	Interval]
n_person	0.079161	0.023398	3.38	0.001	0.033301	0.125021
n_vehicle	-0.91858	0.050802	-18.08	0	-1.01815	-0.81901
intdensity	0.127941	0.008314	15.39	0	0.111646	0.144235
artdensity	0.814966	0.24776	3.29	0.001	0.329366	1.300567
popdensity	46.47951	8.892901	5.23	0	29.04975	63.90928
empft	(dropped)					
emppt	(dropped)					
empwahft	-1.15177	0.278908	-4.13	0	-1.69842	-0.60512
empwahpt	(dropped)					
agebelow1	2.071057	0.40229	5.15	0	1.282582	2.859531
age18_24	0.548662	0.060789	9.03	0	0.429519	0.667806
age25_39	0.165987	0.03512	4.73	0	0.097154	0.234821
age40_54	(dropped)					
ageabove6	-0.13142	0.059848	-2.2	0.028	-0.24872	-0.01412
amp	(dropped)					
pmp	0.475206	0.06589	7.21	0	0.346064	0.604348
male	-0.53661	0.060273	-8.9	0	-0.65475	-0.41848
_IageXte~1	-0.26441	0.2278	-1.16	0.246	-0.71089	0.182067
_IageXte~1	(dropped)					
_IageXte~1	(dropped)					
_IageXte~3	-0.16574	0.10624	-1.56	0.119	-0.37397	0.042488
_IageXte~3	(dropped)					
_IageXte~3	(dropped)					
_IageXte~4	-0.13998	0.115984	-1.21	0.227	-0.3673	0.087345
_IageXte~4	(dropped)					
_IageXte~4	(dropped)					
_IageXte~5	(dropped)					
_IageXte~5	(dropped)					
_IageXte~5	(dropped)					
_IageXte~6	(dropped)					
_IageXte~6	(dropped)					
_IageXte~6	(dropped)					
ageXCloud_	(dropped)					
ageXCloud_	(dropped)					
ageXCloud_	(dropped)					
ageXCloud_	(dropped)					
ageXCloud_	(dropped)					
ageXRain_	(dropped)					
ageXRain_	0.233542	0.151307	1.54	0.123	-0.06302	0.530099
ageXRain_	0.245797	0.168432	1.46	0.144	-0.08432	0.575918
ageXRain_	0.067782	0.052309	1.3	0.195	-0.03474	0.170305
ageXRain_	0.261371	0.118181	2.21	0.027	0.029742	0.493001
ageXShowe	(dropped)					
ageXShowe	(dropped)					
ageXShowe	0.281004	0.238916	1.18	0.24	-0.18726	0.749272
ageXShowe	(dropped)					
ageXShowe	(dropped)					
ageXWind_	(dropped)					
ageXWind_	-0.00566	0.004457	-1.27	0.204	-0.01439	0.003079
ageXWind_	(dropped)					
ageXWind_	(dropped)					
ageXWind_	(dropped)					
_cons	-0.22742	0.150517	-1.51	0.131	-0.52243	0.067584

Appendix B:Nested Logit Modelling Results

tree structure specified for the nested logit model

type2	N		Mode	N	k
Transit	42743	——	Tran	42743	10603
active	37446	┬─	Bike	30049	612
		└─	Walk	7397	2087
Driver	43557	——	AutoDriver	43557	27142
Pass	43557	——	AutoPassenger	43557	3113
			total	167303	43557

k = number of times alternative is chosen
N = number of observations at each level

Iteration 0: log likelihood = -38262.779
Iteration 1: log likelihood = -37287.071 (backed up)
Iteration 2: log likelihood = -34704.991 (backed up)
Iteration 3: log likelihood = -34354.421 (backed up)
Iteration 4: log likelihood = -34270.97 (backed up)
Iteration 5: log likelihood = -34074.372 (backed up)
Iteration 6: log likelihood = -34057.528 (backed up)
Iteration 7: log likelihood = -33997.253 (backed up)
Iteration 8: log likelihood = -33890.161 (backed up)
Iteration 9: log likelihood = -33862.734 (backed up)
Iteration 10: log likelihood = -33806.759 (backed up)
Iteration 11: log likelihood = -33757.967 (backed up)
Iteration 12: log likelihood = -33699.187 (backed up)
Iteration 13: log likelihood = -33672.76 (backed up)
Iteration 14: log likelihood = -33632.399 (backed up)
Iteration 15: log likelihood = -33629.232 (backed up)
Iteration 16: log likelihood = -33611.766 (backed up)
Iteration 17: log likelihood = -33600.911 (backed up)
Iteration 18: log likelihood = -33557.944 (backed up)
Iteration 19: log likelihood = -33527.729 (backed up)
Iteration 20: log likelihood = -33506.151 (backed up)
Iteration 21: log likelihood = -33489.109 (backed up)
Iteration 22: log likelihood = -33465.838 (backed up)
Iteration 23: log likelihood = -33448.8 (backed up)
Iteration 24: log likelihood = -33433.763 (backed up)
Iteration 25: log likelihood = -33394.38 (backed up)
Iteration 26: log likelihood = -33356.713 (backed up)
Iteration 27: log likelihood = -33338.96 (backed up)
Iteration 28: log likelihood = -33331.12 (backed up)
Iteration 29: log likelihood = -33325.909 (backed up)
Iteration 30: log likelihood = -33298.746 (backed up)
Iteration 31: log likelihood = -33277.359 (backed up)
Iteration 32: log likelihood = -33275.12 (backed up)
Iteration 33: log likelihood = -33244.988 (backed up)
Iteration 34: log likelihood = -33198.749 (backed up)
Iteration 35: log likelihood = -33142.38 (backed up)
Iteration 36: log likelihood = -33090.369 (backed up)
Iteration 37: log likelihood = -33073.904 (backed up)

Iteration 38: log likelihood = -33032.307 (backed up)
Iteration 39: log likelihood = -32990.762 (backed up)
Iteration 40: log likelihood = -32985.05 (backed up)
Iteration 41: log likelihood = -32908.702 (backed up)
Iteration 42: log likelihood = -32859.536 (backed up)
Iteration 43: log likelihood = -32811.811 (backed up)
Iteration 44: log likelihood = -32779.755 (backed up)
Iteration 45: log likelihood = -32769.951 (backed up)
Iteration 46: log likelihood = -32738.16 (backed up)
Iteration 47: log likelihood = -32705.866 (backed up)
Iteration 48: log likelihood = -32679.715 (backed up)
Iteration 49: log likelihood = -32657.084 (backed up)
Iteration 50: log likelihood = -32656.957 (backed up)
Iteration 51: log likelihood = -32624.214 (backed up)
Iteration 52: log likelihood = -32596.895 (backed up)
Iteration 53: log likelihood = -32595.752 (backed up)
Iteration 54: log likelihood = -32582.545 (backed up)
Iteration 55: log likelihood = -32561.712 (backed up)
Iteration 56: log likelihood = -32549.056 (backed up)
Iteration 57: log likelihood = -32533.598 (backed up)
Iteration 58: log likelihood = -32524.152 (backed up)
Iteration 59: log likelihood = -32511.539 (backed up)
Iteration 60: log likelihood = -32507.057 (backed up)
Iteration 61: log likelihood = -32505.145
Iteration 62: log likelihood = -32495.047 (backed up)
Iteration 63: log likelihood = -32470.606 (backed up)
Iteration 64: log likelihood = -32454.562 (backed up)
Iteration 65: log likelihood = -32451.362 (backed up)
Iteration 66: log likelihood = -32442.277 (backed up)
Iteration 67: log likelihood = -32431.851 (backed up)
Iteration 68: log likelihood = -32423.226
Iteration 69: log likelihood = -32418.557 (backed up)
Iteration 70: log likelihood = -32414.291
Iteration 71: log likelihood = -32407.077 (backed up)
Iteration 72: log likelihood = -32396.34 (backed up)
Iteration 73: log likelihood = -32384.932 (backed up)
Iteration 74: log likelihood =   -32376.9 (backed up)
Iteration 75: log likelihood = -32366.965 (backed up)
Iteration 76: log likelihood = -32361.378 (backed up)
Iteration 77: log likelihood = -32359.234 (backed up)
Iteration 78: log likelihood = -32357.281
Iteration 79: log likelihood = -32353.984
Iteration 80: log likelihood = -32349.842
Iteration 81: log likelihood = -32347.875
Iteration 82: log likelihood = -32345.151
Iteration 83: log likelihood = -32343.752 (backed up)
Iteration 84: log likelihood = -32342.897
Iteration 85: log likelihood = -32341.663
Iteration 86: log likelihood = -32340.895
Iteration 87: log likelihood = -32339.654
Iteration 88: log likelihood = -32339.633
Iteration 89: log likelihood = -32339.464
Iteration 90: log likelihood = -32339.026
Iteration 91: log likelihood = -32338.024
Iteration 92: log likelihood = -32337.59
Iteration 93: log likelihood = -32336.424

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Iteration 94:  log likelihood = -32336.174
Iteration 95:  log likelihood = -32335.979
Iteration 96:  log likelihood = -32335.803
Iteration 97:  log likelihood =  -32335.66
Iteration 98:  log likelihood = -32335.453
Iteration 99:  log likelihood = -32335.337
Iteration 100: log likelihood = -32335.302
Iteration 101: log likelihood = -32335.288
Iteration 102: log likelihood =  -32335.27
Iteration 103: log likelihood =  -32335.26
Iteration 104: log likelihood = -32335.253
Iteration 105: log likelihood =  -32335.25
Iteration 106: log likelihood = -32335.249
Iteration 107: log likelihood = -32335.248
Iteration 108: log likelihood = -32335.242
Iteration 109: log likelihood = -32335.242
Iteration 110: log likelihood =  -32335.24
Iteration 111: log likelihood = -32335.236
Iteration 112: log likelihood = -32335.236
Iteration 113: log likelihood = -32335.235
Iteration 114: log likelihood = -32335.235
Iteration 115: log likelihood = -32335.235
Iteration 116: log likelihood = -32335.235
Iteration 117: log likelihood = -32335.235
Iteration 118: log likelihood = -32335.235

RUM-consistent nested logit regression        Number of obs      =    167303
Case variable: link                           Number of cases    =     43557

Alternative variable: Mode                    Alts per case: min =         2
                                                             avg =       3.8
                                                             max =         5

                                              Wald chi2(112)  =   13346.32
Log likelihood = -32335.235                   Prob > chi2     =     0.0000

 ( 1) - [Mode]ccost + [Mode]tcost2 = 0
------------------------------------------------------------------------------
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Mode         |
       aivtt |  -.0537031   .0025509   -21.05   0.000    -.0587028   -.0487035
       tivtt |  -.0186225   .0017925   -10.39   0.000    -.0221358   -.0151093
       ccost |  -.6365775   .0189626   -33.57   0.000    -.6737436   -.5994115
      tcost2 |  -.6365775   .0189626   -33.57   0.000    -.6737436   -.5994115
      pkCost |  -.2242705   .0066082   -33.94   0.000    -.2372224   -.2113186
      twaitt |  -.1343615   .0071775   -18.72   0.000     -.148429   -.1202939
      twalkt |  -.0244244   .0038088    -6.41   0.000    -.0318896   -.0169591
       walkt |  -.0892528   .0027713   -32.21   0.000    -.0946845   -.0838211
       biket |  -.0725281    .005617   -12.91   0.000    -.0835371    -.061519
------------------------------------------------------------------------------
type2 equations
------------------------------------------------------------------------------
Transit      |
    n_person |   .1802743   .0107879    16.71   0.000     .1591305    .2014182
   n_vehicle |  -1.000855   .0224851   -44.51   0.000    -1.044925   -.9567852
```

```
  intdensity |   .1107732   .0039542    28.01   0.000     .103023    .1185233
       empft |  -.8073134   .3372932    -2.39   0.017   -1.468396   -.1462309
       emppt |  -.6602156   .3398041    -1.94   0.052   -1.326219    .0057882
     empwahft |  -1.846127   .3663322    -5.04   0.000   -2.564125   -1.128129
     empwahpt |  -1.674454     .47784    -3.50   0.000   -2.611003    -.737905
  agebelow18 |   1.679701   .3479161     4.83   0.000     .997798    2.361604
    age18_24 |    1.09254   .0669661    16.31   0.000    .9612892    1.223791
    age25_39 |   .2765151   .0480254     5.76   0.000     .182387    .3706432
    age40_54 |   .0004323   .0490374     0.01   0.993   -.0956791    .0965438
  ageabove65 |  -.3158464   .1542686    -2.05   0.041   -.6182074   -.0134855
       _cons |   .6446596   .4004825     1.61   0.107   -.1402717    1.429591
-------------+----------------------------------------------------------------
active       |
    n_person |   .0450963   .0207885     2.17   0.030    .0043516    .0858411
   n_vehicle |  -.9393566   .0449318   -20.91   0.000   -1.027421   -.8512918
  intdensity |   .1546575   .0067821    22.80   0.000    .1413649    .1679502
       empft |   .0012333   .6717162     0.00   0.999   -1.315306    1.317773
       emppt |   .3412668   .6746343     0.51   0.613   -.9809922    1.663526
     empwahft |  -.8470042    .707921    -1.20   0.232   -2.234504    .5404953
     empwahpt |  -.6379359   .8774788    -0.73   0.467   -2.357763    1.081891
  agebelow18 |    1.70666   .4067234     4.20   0.000    .9094971    2.503824
    age18_24 |   1.029328   .1221894     8.42   0.000    .7898409    1.268815
    age25_39 |   .6071126   .0901934     6.73   0.000    .4303368    .7838884
    age40_54 |   .2271616   .0919841     2.47   0.014     .046876    .4074471
  ageabove65 |  -.6559727   .2785269    -2.36   0.019   -1.201875   -.1100701
       _cons |  -1.384567   .7715237    -1.79   0.073   -2.896726    .1275917
-------------+----------------------------------------------------------------
Driver       |
    n_person |  (base)
   n_vehicle |  (base)
  intdensity |  (base)
       empft |  (base)
       emppt |  (base)
     empwahft |  (base)
     empwahpt |  (base)
  agebelow18 |  (base)
    age18_24 |  (base)
    age25_39 |  (base)
    age40_54 |  (base)
  ageabove65 |  (base)
       _cons |  (base)
-------------+----------------------------------------------------------------
Pass         |
    n_person |    .340369   .0146291    23.27   0.000    .3116964    .3690415
   n_vehicle |  -.7395829   .0298996   -24.74   0.000    -.798185   -.6809808
  intdensity |   -.009339   .0058279    -1.60   0.109   -.0207615    .0020834
       empft |  -.5385356   .4752158    -1.13   0.257   -1.469941    .3928702
       emppt |  -.4298082   .4773176    -0.90   0.368   -1.365333     .505717
     empwahft |  -.7915272   .5106371    -1.55   0.121   -1.792357    .2093031
     empwahpt |  -.4242064   .5983989    -0.71   0.478   -1.597047    .7486338
  agebelow18 |   2.680214   .3265274     8.21   0.000    2.040232    3.320196
    age18_24 |   .9571127   .0893463    10.71   0.000    .7819972    1.132228
    age25_39 |   .0359382   .0701383     0.51   0.608   -.1015305    .1734068
    age40_54 |  -.2363173   .0713138    -3.31   0.001   -.3760898   -.0965448
  ageabove65 |   .1447363   .2083319     0.69   0.487   -.2635867    .5530593
       _cons |  -1.545395   .5714154    -2.70   0.007   -2.665348   -.4254412
```

```
------------------------------------------------------------------------------
Mode equations
------------------------------------------------------------------------------
AutoDriver   |
  artdensity |     (base)
        male |     (base)
         amp |     (base)
         pmp |     (base)
  tempbelow0 |     (base)
     temp1_5 |     (base)
    temp6_10 |     (base)
   temp11_15 |     (base)
   temp16_20 |     (base)
   temp21_25 |     (base)
   temp31_35 |     (base)
tempaabove35 |     (base)
       cloud |     (base)
        rain |     (base)
     showers |     (base)
         sun |     (base)
Pearson_wind |     (base)
-------------+----------------------------------------------------------------
AutoPassen~r |
  artdensity |   .4977998   .1699659     2.93   0.003     .1646729    .8309268
        male |  -1.401514   .0423338   -33.11   0.000    -1.484487   -1.318541
         amp |  -.1654192   .0499261    -3.31   0.001    -.2632725   -.0675659
         pmp |   .1154107    .052624     2.19   0.028     .0122697    .2185518
  tempbelow0 |   .3943092   .3179661     1.24   0.215    -.2288929    1.017511
     temp1_5 |   .3427395   .2972076     1.15   0.249    -.2397767    .9252556
    temp6_10 |   .2520655    .295948     0.85   0.394    -.3279819    .8321129
   temp11_15 |   .1604239   .2960177     0.54   0.588    -.4197601    .7406079
   temp16_20 |   .1761112   .2975742     0.59   0.554    -.4071235    .7593458
   temp21_25 |   .0890255    .315967     0.28   0.778    -.5302584    .7083094
   temp31_35 |   .6511099   .5459892     1.19   0.233    -.4190093    1.721229
tempaabove35 |   .5311217   .6221705     0.85   0.393     -.68831     1.750554
       cloud |  -.1076492   .0537699    -2.00   0.045    -.2130363   -.0022621
        rain |  -.1394928   .0776303    -1.80   0.072    -.2916453    .0126597
     showers |  -.1192802   .1158453    -1.03   0.303    -.3463329    .1077724
         sun |  -.0115703   .0032523    -3.56   0.000    -.0179447   -.0051958
Pearson_wind |  -.0018773   .0019592    -0.96   0.338    -.0057172    .0019625
-------------+----------------------------------------------------------------
Bike         |
  artdensity |  -1.377567   .3470884    -3.97   0.000    -2.057848   -.6972859
        male |   .3192059   .0914837     3.49   0.000     .1399011    .4985107
         amp |  -.4030681   .1036569    -3.89   0.000    -.6062319   -.1999043
         pmp |   -.012464   .1102141    -0.11   0.910    -.2284796    .2035516
  tempbelow0 |  -2.164985   .4539395    -4.77   0.000     -3.05469    -1.27528
     temp1_5 |   -1.77431   .3437977    -5.16   0.000    -2.448141   -1.100479
    temp6_10 |  -1.812535   .3390666    -5.35   0.000    -2.477093   -1.147977
   temp11_15 |   -1.50404    .336741    -4.47   0.000     -2.16404   -.8440396
   temp16_20 |  -1.238692   .3394495    -3.65   0.000    -1.904001   -.5733831
   temp21_25 |  -1.116167   .3793201    -2.94   0.003    -1.859621   -.3727135
   temp31_35 |  -1.310085   1.087884    -1.20   0.228    -3.442298    .8221281
tempaabove35 |  -1.166979   1.072122    -1.09   0.276      -3.2683    .9343418
       cloud |  -.1599496   .1123588    -1.42   0.155    -.3801689    .0602696
        rain |  -.4151776   .1825055    -2.27   0.023    -.7728817   -.0574734
```

```
     showers |  -.5709691   .2713827    -2.10   0.035    -1.102869   -.0390688
         sun |  -.0174225   .0063466    -2.75   0.006    -.0298616   -.0049834
Pearson_wind |  -.0079893   .0043923    -1.82   0.069    -.0165982    .0006195
-------------+----------------------------------------------------------------
Tran         |
  artdensity |   .8175761   .1193681     6.85   0.000     .5836189    1.051533
        male |  -.7670914   .0275825   -27.81   0.000    -.8211521   -.7130307
         amp |  -.3990805   .0413462    -9.65   0.000    -.4801176   -.3180435
         pmp |   .3653327    .037088     9.85   0.000     .2926415    .4380239
  tempbelow0 |   .0591241   .2092378     0.28   0.778    -.3509744    .4692227
     temp1_5 |   .1018983   .1900769     0.54   0.592    -.2706456    .4744422
    temp6_10 |   .1164214   .1889712     0.62   0.538    -.2539554    .4867981
   temp11_15 |   .1523606   .1887077     0.81   0.419    -.2174998    .5222209
   temp16_20 |   .1951662   .1896948     1.03   0.304    -.1766287    .5669611
   temp21_25 |   .2242739   .1981939     1.13   0.258    -.1641791    .6127269
   temp31_35 |   .2891774   .3875984     0.75   0.456    -.4705014    1.048856
tempaabove35 |   .5794217   .3695353     1.57   0.117    -.1448543    1.303698
       cloud |  -.0247242   .0373316    -0.66   0.508    -.0978928    .0484444
        rain |   .0149706   .0532787     0.28   0.779    -.0894537    .1193949
     showers |  -.0243249   .0776584    -0.31   0.754    -.1765326    .1278828
         sun |  -.0040078   .0020335    -1.97   0.049    -.0079934   -.0000222
Pearson_wind |   .0017322   .0013243     1.31   0.191    -.0008633    .0043278
-------------+----------------------------------------------------------------
Walk         |
  artdensity |   .5984244   .2366418     2.53   0.011      .134615    1.062234
        male |  -.4704292   .0633173    -7.43   0.000    -.5945288   -.3463296
         amp |   .0555212    .077888     0.71   0.476    -.0971366    .2081789
         pmp |   .5607895   .0813753     6.89   0.000     .4012969    .7202822
  tempbelow0 |   1.680245   .4279404     3.93   0.000     .8414975    2.518993
     temp1_5 |   1.242741   .3855194     3.22   0.001      .487137    1.998345
    temp6_10 |   1.439192   .3835184     3.75   0.000     .6875101    2.190875
   temp11_15 |   1.409497    .384642     3.66   0.000     .6556125    2.163381
   temp16_20 |   1.552185   .3885561     3.99   0.000     .7906287    2.313741
   temp21_25 |   1.272755   .4223371     3.01   0.003     .4449897    2.100521
   temp31_35 |   1.992632   .9177508     2.17   0.030     .1938731     3.79139
tempaabove35 |   2.196362   .8340205     2.63   0.008     .5617118    3.831012
       cloud |   .1058046   .0883673     1.20   0.231    -.0673921    .2790012
        rain |   .3862484   .1241604     3.11   0.002     .1428984    .6295984
     showers |   .2457767   .1690385     1.45   0.146    -.0855327    .5770861
         sun |  -.0006901   .0045041    -0.15   0.878     -.009518    .0081378
Pearson_wind |  -.0029103   .0030432    -0.96   0.339    -.0088749    .0030543
------------------------------------------------------------------------------
dissimilarity parameters
------------------------------------------------------------------------------
type2        |
/Transit_tau |          1   96187.93                     -188523.9    188525.9
 /active_tau |   .9827864   .0580966                      .8689192    1.096654
 /Driver_tau |          1          .                             .           .
   /Pass_tau |          1          .                             .           .
------------------------------------------------------------------------------
LR test for IIA (tau = 1):           chi2(2) =     0.09   Prob > chi2 = 0.9575
```

Appendix C: Model Validity Test Results

1. Without cost constraints

1.1. Using 100% of sample

Rho-squared: 0.3
Auto Value of Time: $45.53
Transit Value of Time: $0.84

		Observed						
		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total Predicted	Mode share
Predicted	Transit	4811.656	175.9758	290.9755	4519.195	805.1974	10603	24.34%
	Bike	172.4656	28.40732	66.01641	304.9823	40.12836	612	1.41%
	Walk	166.2869	59.44635	971.5519	752.1003	137.6146	2087	4.79%
	Adtuo Driv	4587.516	310.4787	653.3769	19818.45	1772.179	27142	62.31%
	Auto Passe	865.0749	37.69188	105.0793	1747.273	357.8809	3113	7.15%
Total Observed		10603	612	2087	27142	3113	43557	
% correctly predicted		**45%**	**5%**	**47%**	**73%**	**11%**	**60%**	

aivtt	-0.06569
tivtt	-0.01029
ccost	-0.08657
tcost	-0.73407

1.2. Using 75% of sample

Rho-squared: 0.3
Auto Value of Time: $47.19
Transit Value of Time: $0.73

		Observed						
		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total Predicted	Mode share
Predicted	Transit	3602.634	127.9116	213.5033	3345.369	617.5822	7907	24.29%
	Bike	127.0121	22.42494	51.54596	233.3849	30.63217	465	1.43%
	Walk	119.9672	47.40954	722.156	556.92	99.54725	1546	4.75%
	Adtuo Driv	3402.843	239.1739	481.2832	14833.81	1325.891	20283	62.32%
	Auto Passe	654.5443	28.08001	77.51151	1313.517	271.3476	2345	7.21%
Total Observed		7907	465	1546	20283	2345	32546	
% correctly predicted		**46%**	**5%**	**47%**	**73%**	**12%**	**60%**	

1.3. Checking model predictability with the remaining 25%

		Observed						
		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total Predicted	Mode share
Predicted	Transit	1213.898	48.5093	79.15921	1146.124	186.6281	2674	24.29%
	Bike	44.54954	6.825521	19.52479	82.12793	9.923864	163	1.48%
	Walk	42.50525	10.93337	245.1531	199.6852	38.29727	537	4.87%
	Adtuo Driv	1173.787	70.63244	168.655	4975.093	443.8767	6832	62.05%
	Auto Passe	221.261	10.09937	28.50797	455.9698	89.27406	805	7.31%
Total Observed		2696	147	541	6859	768	11011	
% correctly predicted		45%	5%	45%	73%	12%	59%	

2. With cost constraints

2.1. Using 100% of sample

Rho-squared: 0.23
Auto Value of Time:$12 .93
Transit Value of Time: $2.47

		Observed						
		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total Predicted	Mode Share
Predicted	Transit	4662.6	180.4	298.0	4639.0	823.1	10603	24.34%
	Bike	180.0	28.0	66.1	298.4	39.5	612	1.41%
	Walk	172.9	59.5	972.6	744.6	137.3	2087	4.79%
	Adtuo Drive	4669.4	307.6	652.9	19748.4	1763.8	27142	62.31%
	Auto Passenger	918.2	36.5	97.5	1711.5	349.3	3113	7.15%
Total Observed		10603	612	2087	27142	3113	43557	
% correctly predicted		44%	5%	47%	73%	11%	59%	

aivtt	-0.05745
tivtt	-0.01097
ccost	-0.2667
tcost	-0.2667

2.2. Using 75% of sample

Rho-squared: 0.23
Auto Value of Time: $ 12.55
Transit Value of Time: $ 2.21

		Observed						
		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total Predicted	Mode share
Predicted	Transit	3487.247	131.1724	219.2762	3436.68	632.6246	7907	24.29%
	Bike	133.0123	22.19116	51.4806	228.1503	30.16566	465	1.43%
	Walk	125.1395	47.43388	722.9008	551.2555	99.27044	1546	4.75%
	Adtuo Driv	3465.059	237.0321	480.8228	14782.3	1317.785	20283	62.32%
	Auto Passe	696.5421	27.1704	71.51963	1284.614	265.1538	2345	7.21%
Total Observed		7907	465	1546	20283	2345	32546	
% correctly predicted		44%	5%	47%	73%	11%	59%	

2.3. Checking model predictability with the remaining 25%

		Observed						
		Transit	Bike	Walk	Auto Drive	Auto Passenger	Total Predicted	Mode share
Predicted	Transit	1182.979	50.02584	81.23936	1182.458	191.5842	2688	24.41%
	Bike	46.35503	6.75334	19.51743	80.208	9.791612	163	1.48%
	Walk	43.74908	10.95224	246.0349	197.5458	38.32049	537	4.87%
	Adtuo Driv	1190.072	69.60234	167.8959	4954.232	441.1873	6823	61.97%
	Auto Passe	232.8452	9.666235	26.3125	444.5563	87.11641	800	7.27%
Total Observed		2696	147	541	6859	768	11011	
% correctly predicted		44%	5%	45%	72%	11%	59%	

Conclusions

- Keep the constrained model since it gives a more reasonable value of time for transit. The rho-squared of non-constrained is better, but the model's prediction success is the same so no big diff.

- When the model is applied to the 25% hold-out sample the prediction results are very similar to those coming out of the 100% sample