MODELLING THE IMPACT OF WEATHER ON ACTIVE TRANSPORTATION

SANEINEJAD, Sheyda. M.A.Sc. Candidate, University of Toronto, Department of Civil Engineering.35 St. George St., Toronto, Ontario, Canada. M5S 1A4. E-mail: s.saneinejad@utoronto.ca

KENNEDY, Christopher. Associate Professor, Department of Civil Engineering, University of Toronto, 35 St. George Street, Toronto, Canada, M5S 1A4. E-mail: christopher.kennedy@utoronto.ca

ROORDA, Matthew J, Assistant Professor, Department of Civil Engineering, University of Toronto, 35 St. George Street, Toronto, Canada, M5S 1A4. E-mail: roordam@ecf.utoronto.ca

ABSTRACT

This study introduces a weather sensitive mode-choice model developed using a combined database of travel activity and the corresponding historical hourly weather conditions in the city of Toronto. Weather features integrated in the model include categories of temperature ranges, wind speed, and four precipitation conditions. Two sub models are also developed in order to study the impact of the interaction between weather conditions and different age and gender groups on active transportation mode choice. Results of this research confirm that the impact of weather on active modes of transportation is significant enough to deserve attention at the research, data collection and planning levels. From a policy perspective, these results can significantly help with more successful active transportation promotional policies. Additionally, by highlighting some of the behavioural differences between pedestrians and cyclists, this paper can contribute to better and more effective policies and infrastructure provision. Lastly, through analysis of the impact of weather on all other modes of travel this research provides an area of improvement for future travel surveys collected for Toronto and other regions

Keywords: active transportation, mode choice modelling, impact of weather conditions

INTRODUCTION

Making non-motorized modes transportation feasible alternatives for people's daily travel is a large part of the solution for worldwide problems such as oil depletion, climate change, road congestion and increase in obesity. 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.

The primary objective of this paper is to investigate the influence of weather conditions on walking and cycling mode choice. Research, introduced in the following section, suggests that this impact is significant. However, there are certain gaps in existing research that this study aims to fill. The data used in most of the existing research on this topic are either too aggregate to include detailed enough weather condition and trip specific characteristics or so specific that they fail to capture the influence of socioeconomic characteristics of trip makers and characteristics of all other alternative modes. By overcoming these drawbacks this paper aims to describe how mode choice decisions of different demographic groups are affected by weather conditions, especially for the walk and bike mode. This is anticipated to help gear promotional policies towards appropriate audiences. Additionally, in some infrastructure provision conversations the bicycle and walk travel modes are sometime combined for convenience and simplification. A secondary objective of this paper is therefore to highlight some of the behavioural differences between pedestrians and cyclists in order to help planners developed more successful policies and provide more effective infrastructure. Lastly, the authors hope 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.

To meet the objectives highlighted above the authors explore multinomial logit (MNL) and nested logit modelling approaches 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. The focus of this research is to model behaviour of trip makers who are not captive to a limited choice set of alternatives. As a result, the sample is restricted to individuals who have 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 travel survey of the Toronto region. 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.

The following section of the paper introduces some of the existing research on impacts of weather on active transportation and highlights some of the gaps. This is followed by a summary of the various datasets that have been combined to make this research possible. An overview of the theory and methodology behind the modelling work is then presented, followed by analysis of model results. Lastly, major findings on mode choice behaviour of different age and gender groups, in addition to differences between the walking and cycling mode are summarized along with indications of where this research is headed in the future.

BACKGROUND

As with any transportation mode choice analysis, in studying active transportation the relative out-of-pocket cost and travel time of all feasible transportation alternatives are important 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 traditional 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 conducted by Dill & Carr (2003), Winters et al. (2007), and Parkin et al. (2008), amongst others. Depending on the nature of the study these range in level of detail 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. One group contains those looking at national travel behaviour data, which could be rich on 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.

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. 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 on 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 data and limited socioeconomic variables.

A 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. Work of 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.

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. 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.

The second group of literature introduced below tackles some of these drawbacks 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-maker's 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 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 affect 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, utilized in the above study, can be useful in gaining insight into people’s perception of weather conditions, in addition to collecting data on hypothetical situations. Cools et al. (2008) 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 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.

The higher number of cycling related studies in general may be due to the fact that the higher speed of cycling makes it a competitive mode with transit and even auto while walking is often not considered an alternative mode for longer trips. That said, it should be noted that more than a quarter of trips in the USA are to destinations less than a mile away (Pucher & Renne 2003), and 75% of such trips are made using the automobile (Killingsworth et al.

2003). It is evident that, as suggested by Morency et al. (2009) walking can be a viable mode for such shorter distance trips. Additionally, when comparing the impact of different variables on walking and cycling modes it is important to separate the two. Although these modes have traditionally been coupled together for convenience and simplification, there are fundamental differences between the two that need to be further explored. Factors such as gender, street network and topography, for instance, influence these two modes quite differently. It is anticipated that different weather conditions may have different influences on walking and cycling as well.

Looking at the literature introduced in this section it is evident that there are some gaps in the current state of research on the impact of weather on walking and cycling. In spite of these gaps in current research, the literature introduced above mostly suggests that weather has a significant impact on non-motorized modes of transportation, namely walking and cycling. One implication that this has is with regards to travel survey data, which are collected during a short period of time of the year for most regions. For the Toronto region, for instance, the Transportation Tomorrow Survey is conducted during September to early December. This is in order to avoid anomalies due to vacation travelling in the summer and during the Christmas holidays, but also to capture trips made only during relatively mild weather by avoiding snowy and sub-zero conditions. One could argue however, that a true representation of travel patterns within the region should capture variations in trip rates of different modes as a result of change in weather conditions. This would consequently result in better and more accurate travel demand models as argued by Aultman-Hall et al. (2009).

Further research into the impact of weather conditions on mode choice of various population groups, such as age groups or genders, can contribute greatly to policies and programs aimed at promoting non-motorized modes of transportation. Additionally, infrastructure provision and maintenance operations can also benefit from further insight into trip makers' preferences and choices in various weather conditions.

DATA

Travel Survey Data

The travel data used to estimate the models presented in this paper is sampled from the 2001 Transportation Tomorrow Survey (TTS). The TTS is a 5% trip diary survey of the Greater Toronto Area residents 11 years of age and older that is conducted every 5 years (Data Management Group 2001).The five modes of auto driver, auto passenger, transit, walk and bicycle are sampled.

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. 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 to ensure more 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. As a result, only work trips originated from or destined to home are modelled here. Table 1 illustrates a summary of sample size reductions as a result of the above constraints and the final resulting sample.

Table 1 - 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%)

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. Off-peak and afternoon peak networks for the GTA are 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 only 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) for auto passenger, walk and bicycle are assumed to be zero. Similarity 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.

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. Hourly weather data corresponding to this period, collected at the Toronto Pearson International Airport weather station, which includes temperature, wind speed, humidity and sky conditions was purchased from Environment Canada (Environment Canada 2008). Temperatures are adjusted for wind-chill and humidex based on equations provided by Environment Canada (Environment Canada 2010). Several verbal descriptions are used for the sky conditions in the raw weather data. These were reduced by the authors to five mutually exclusive categories of clear, cloud, rain, shower and snow. Table 2 provides a breakdown of the estimated sample by these sky conditions and nine temperature categories.

Table 2 - 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**

Note: Wind speed is another weather related variable used in the model. Wind speeds range between 0 and 70 km/hr, with an average of 17 km/hr. Since this information is available for every trip, sample counts are not provided in the table for the wind speed variable.

In addition to the temperature categories and sky conditions reported above, wind speed data were also available and used in the analysis. Since the data collection period was during the Fall and Spring seasons, very few observations are made in snowy conditions. As a result, the authors chose not to include the snow variable in the model estimations. This also eliminates complications with high correlation between the snow and the sub-zero temperatures.

METHODOLOGY

The decision to take one mode of travel over others is commonly treated as a utility maximization process. In such a process, according to utility maximization theory, the trip maker is assumed to be perfectly rational and by weighing the positives and negatives of all modes chooses the mode that results in maximum 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.

The logit model assumes a Type 1 Extreme-Value distribution of the error terms. The resulting IIA assumption sets a major constraint in MNL models by implying that the error terms are independently and identically 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 authors hypothesize that the walk and bike modes have correlated unobserved characteristics. 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 is allowed among lower level choices under the same grouping, allowing them to share some common attributes based on their grouping. Figure 1 illustrates a hypothetical two-level nested structure. Alternatives 1 and 2 are grouped together under Nest 1 based on the assumption of the modeler 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.

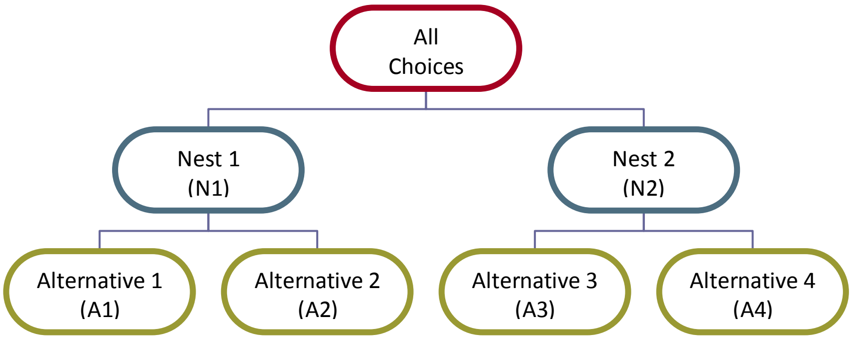

Figure 1 Graphical Representation of Nested Modelling Structure

Given that V_{it} is the observable utility the probability of an individual choosing upper level choice *N* is given by

$$P_N = \frac{e^{V_{it} + \Phi I_N}}{\sum_{N'} e^{V_{N'} + \Phi I_{N'}}}, \qquad (1)$$

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

$$P_{A|N} = \frac{e^{\frac{V_{A|N}}{\Phi}}}{\sum_{A'} e^{\frac{V_{A'|N}}{\Phi}}}. \qquad (2)$$

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

$$P_{NA} = P_N . P_{A|N} \qquad (3)$$

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

$$I = \log \sum_{A'} e^{\frac{V_{A'|N}}{\Phi}} \qquad (4)$$

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.

Specifications of Models

In addition to experimenting between the basic MNL and the nested structure two sub models are also 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 base alternative and variables. The parameters for driving cost, parking cost and transit cost are constrained to be the same. Auto drive is set as the base mode relative to which parameters are estimated for all other modes. The temperature category of 26 to 30 degrees is set as the base temperature category. This 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 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.

Two nested structures were evaluated in the modelling 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 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 mode is treated as a degenerate nest and is separated from the two other motorized modes of driver and passenger.

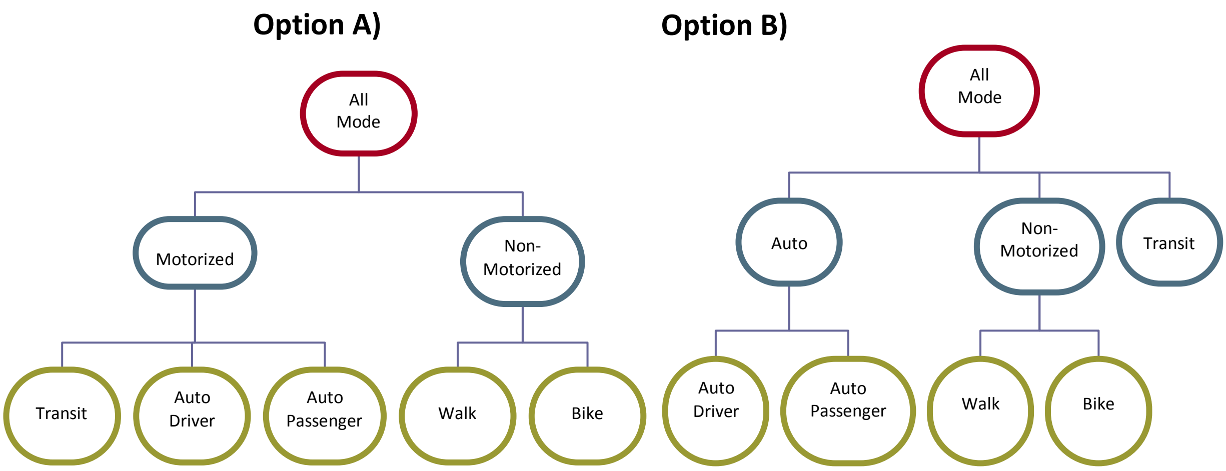

Figure 2. Nested Model Structure Options A) and B)

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 temperature variables would have to be interacted with six dummy age variables, resulting in 36 categories with few data points. To tackle this issue both of the age and temperature categories were aggregated. Instead of the original nine temperature categories illustrated in Table 2 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 resulting in 18 categories.

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.

MODEL RESULTS AND DISCUSSION

After exploring the two nested structure introduced in Figure 2 and experimenting with shifting various variables between the upper and lower nests the authors conclude 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, Ewing et al. (2004) in a study of student mode choice came to similar conclusions after experimenting with some nested structures for grouping non-motorized modes together. This further supports the idea that walking and cycling share no similarities in terms of unobserved characteristics of trip makers who engage in these modes.

Results of the MNL model estimation are presented in

Table 3. 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 UK Department for Transport (2006) 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. (2006), report larger ρ^2 values of above 0.5, indicating better goodness of fit.

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

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 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.

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 and more frequent transit stops. Connectivity of the street network, represented by the intersection density variable, most significantly influences bicycle modeshare followed by walking and transit to lesser extents. Lastly, arterial density, which is a measure 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 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 pedestrians trips, in addition to more busy and secure walking environments, compared to side roads. Moreover, it is likely that the motorized modes are positively affected by more arterial roads since it implies faster travel times.

Socioeconomic variables

Estimated parameters suggest that people in larger households tend to drive less and be auto passengers or transit riders, followed by walk and bike to lesser extents. Additionally, the more vehicles available per household the higher the chances of driving compared to all other modes. Individuals working full time at home are least likely to take 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 are more likely to drive than to be auto passengers, take transit or walk, in descending order, but more likely to bike, pointing at the large male to female ratio of cyclists in Toronto. As expected, younger people are more likely to be auto passengers take transit and walk. Lastly, the tendency to walk, bike and take transit drops as people get older, most drastically for the bike mode past the age of 55.

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 degrees the bicycle mode becomes insensitive to temperature, while for temperatures below 15 the utility of cycling gradually decreases. The walk mode is only sensitive to temperatures of 1 to 5 degrees. Moreover, compared to the parameter for walk mode in the 1 to 5 degrees 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 not in the form of snow and is therefore more of a deterrent.

Wind speed negatively affects cycling twice as much as walking, which is likely 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.

Table 3 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 indicator with two asterisk (**) are significant at 90%.

The probability of being an auto passenger gradually decreases as temperature increases. However, this decision is not affected by temperatures above 10 degrees. It is also surprising to see that the transit mode is seemingly insensitive to all temperatures relative to the auto mode. 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 of these results will be provided later in the discussion of the interaction models.

The prediction success result for trip outcomes used in parameter estimation, shown in

Table 4, indicate that 59% of the modes 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 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 transit trips mis-predicted as bike trips.

Table 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%**

Interaction Models Results

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. 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 3 and therefore are not discussed here. Similar adjusted ρ^2 values and prediction success results as those presented in Table 4 are also calculated for the interaction models.

Gender interaction model

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

There are some known gender differences in mode choice, especially in cycling in North America, as studied by researchers such as Emond et al. (2009). However, even after controlling for general gender effects on mode choice (see gender coefficients in Table 5), females' utility for the bike mode is about 1.5 times more negatively affected by low temperatures than males. Interestingly however, it appears that males' change in likelihood to bike 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.

Parameters also suggest that the utility of walking is more positively affected by precipitation conditions compared to the auto mode. This is similar to the results of the basic MNL model and makes little logical sense aside from potential impact of cyclists switching to walking in sub-optimal weather conditions.

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 below 20 degree temperatures. These effects are however different in magnitude for male and female trip makers. This explains why, when grouped together, they would be estimated to be insignificant. As temperatures drop the likelihood of both genders to take transit is negatively affected.

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. The interaction model results suggest that after controlling for general gender effects on transit mode choice males are likely to switch to transit from auto in cloudy and rainy conditions, while females are insensitive to all sky conditions. Similarly, the auto passenger mode results show that in precipitation conditions and high wind speeds being an auto passenger becomes more attractive than driving for male trip makers, while females are again insensitive. This may suggest that while taking transit or being an auto passenger may be a more routine mode of commuting for females, males use transit and auto passenger as an alternative mode in sub-optimal conditions. The auto passenger results in the interaction model make more sense than those suggested by the basic MNL model. Results also suggest that, compared to males, it is more likely for females to switch from auto drive to auto passenger in cold and very hot temperatures.

Table 5 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 and how much explained by the weather variables
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.

Age Interaction Model

Several parameters of interaction terms between temperature and age categories come out to be insignificant due to very disaggregate data and small sample sizes in this case. Nevertheless, results of the age interaction model, presented in Table 6, 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. Cyclists of 54 years old and younger are negatively influenced by temperatures of below 20 degrees. This influence is most pronounced for younger cyclists of below 25 years old. Similar results are evident for the walk mode for temperatures below 5 degrees. 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.

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.

Table 6 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*
Temperature	**6 to 20**					
Temperature	**21 to 30**	base	base	base	base	base
Temperature	**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**	
Temperature	**6 to 20**					
Temperature	**21 to 30**	base	base	base	base	base
Temperature	**above 30**					
	wind					
	cloud					
	rain	0.308*				
	shower					

Walk

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

Bike

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

$\rho^2 = 0.22$

Note: 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.

Since observations for male and female trip makers are again grouped together in this interaction model, most temperature 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 the below 25 years and 55 to 65 years age groups, cold temperatures appear to negatively impact transit riders and encourage them to drive. 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 the below 25 year age group is affected by rainy conditions. Results suggest that these individuals tend to switch to transit from driving under rainy conditions.

As reported earlier, results of the age interaction model suggested that very warm temperatures encourage females to switch to being auto passengers from auto drivers. 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 are also likely to switch to being auto passengers in hot temperatures, while all other age groups are insensitive to these conditions.

CONCLUSIONS AND FUTURE WORK

This study explores the impact of weather conditions on active modes of transportation using the multinomial logit (MNL) and nested logit modelling approaches. While the nested structure proved to be unsuitable for this purposes the MNL model offers several interesting results. In addition to the basic MNL model, two sub models are developed in order to explore interaction of demographic groups with weather conditions. Results of these two models provide further insight into mode choice behavioural changes due to weather.

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

In addition to the anticipated impacts of weather condition on walking and cycling modes 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 degrees. Furthermore, walk trips are only sensitive to temperature below 5 degrees and to a smaller extent than bike trips. Wind speeds negatively influence 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 are more likely to switch to transit mode 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.

Some of the parameters for non-weather related variables provide further insight into differences between walking and cycling modes. These include population density, arterial density and intersection density. Arterial density is used as a measure of motorized traffic flow while intersection density offers a measure of street connectivity. Results suggest that while the walk mode is strongly affected by population density, cycling is insensitive to this measure. Additionally, while the walk mode share benefits from increased arterial density, the bike mode is negatively affected by presence of arterial roads. Lastly, intersection density appears to positively influence cyclists more than pedestrians.

It is evident that the impact of weather on mode choice, 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 paper 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 significantly help with making active transportation promotional policies more successful by targeting specific age and gender groups. Additionally, the bicycle and walk travel modes are sometimes grouped together for convenience and simplification. By highlighting some of the behavioural differences between the two, this paper can contribute to better and more effective policies and infrastructure provision. Lastly, it is evident that all modes of travel are affected to a certain extent by weather. This provides 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 is collected. This also further impacts the accuracy of forecast models.

Due to limited data the authors were unable to look more closely at the impact of sub zero temperatures and winter conditions on non-motorized mode choice. Another limitation to this study may be the decision to group all transit modes. Works of Bento et al. (2005) on transit ridership suggests that weather influences bus and rail transit quite differently.

The next component of this research will be focusing on applying the developed models to evaluating impacts on mode choice as a result of the anticipated change in the climate of Toronto for the remainder of the century. It would also be interesting to investigate how trip-makers' response to weather in different cities is reflected in their mode-share compared to Toronto.

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