INVESTIGATING THE CAPACITY OF CONTINUOUS HOUSEHOLD TRAVEL SURVEYS IN REPLACING TRADITIONAL CROSS-SECTIONAL SURVEYS

by

WAFIC EL-ASSI

A thesis submitted in conformity with the requirements
for the degree of Master of Applied Science

Department of Civil Engineering
University of Toronto

Investigating the Capacity of Household Travel Surveys in Replacing Traditional Cross-Sectional Surveys

Wafic El-Assi

Master of Applied Science

Department of Civil Engineering
University of Toronto

2016

Abstract

In this thesis, the capacity of continuous surveys in replacing cross-sectional surveys is examined. A flexible framework for both cross-sectional and continuous household travel survey sample size determination is proposed. After that, the state of practice of continuous surveys is closely examined. It is believed that the main advantage of continuous surveys is the availability of data over a continuous spectrum of time. This claim is put to the test by estimating mixed effects models on different levels using the Montreal Continuous Survey data. The use of the mixed effects econometric framework allows for partitioning the variance of the dependent variable to a set of grouping factors, such as time periods and spatial units, enabling the understanding of the underlying causes of variation in travel behavior. The thesis concludes that the temporal variability in trip behavior is only observed when modelling on the regional or modal level.

Acknowledgments

All praise is due to Allah; the most gracious, the most merciful.

Where do I start… I will forever be grateful for the love and support that I have experienced on a daily basis at the University of Toronto Transportation Research Institute. I started my journey in this lab as a naïve undergraduate researcher, drawing bike lanes on ArcMap GIS. It is truly an amazing feeling to have had the opportunity to reach this milestone.

I am forever indebted for the guidance, support, and mentorship of my supervisor Professor Khandker Nurul Habib. It is he who has taught me how to walk before I can run in the world of transportation research. Thank you, sir, for your constant encouragement and perpetual enthusiasm.

I am also very grateful for the constant feedback I have received from Professor Eric Miller throughout my tenure as a MASc student. Your wealth of experience has always been an inspiration. Further, I would like to acknowledge the help of Professor Catherine Morency in the field of survey methods, and the tutelage of Professor Birsen Donmez in mixed effects models.

As for my friends and colleagues in the ITS lab, my biggest thanks go to Md. Sami Hasnine and Adam Weiss. Their constant encouragement and loyal friendship were a definite factor in my success. I thank Siva for his constructive feedback and Tian for helping me with a graph in this thesis. In addition, I have immensely benefited from the experience and wisdom of Aya, Toka, Islam, Tamer and Ehab. I would also like to extend my gratitude to Greg, Mehdi, Moein, Ahmed, and the rest of ITS lab team.

No personal acknowledgement chapter would be complete without the mention of my two wonderful mentors: Mohamed Salah and Mohamed Soliman. Without the two of you, I would have never been exposed to the world of graduate research.

Last but most important, I extend my love and appreciation to my dear parents Mohammed and Nisrean, and to my amazing wife Mariam. Our many Skype calls are what kept me going.

Table of Contents

List of Tables

List of Figures

Glossary

OD	Origin-Destination
TTS	Transportation Tomorrow Survey
GTA	Greater Toronto Area
GTHA	Greater Toronto and Hamilton Area
NHTS	National Household Travel Survey
CBD	Central Business District
APE	Absolute Percentage Error
MAPE	Mean Absolute Percentage Error
CV	Coefficient of Variation
MVN	Multivariate Normal
NMS	National Mobility Survey
NTS	National Travel Survey
HTS	Household Travel Survey
GMA	Greater Metropolitan Area
GSMR	Greater Sydney Metropolitan Region
SD	Statistical Division
SSD	Statistical Subdivisions
SLA	Statistical Local Areas
TZ	Traffic Zones

RSE	Residual Standard Errors
AMT	Agence Métropolitaine de Transport
RSG	Resource Systems Group
GLMM	Generalized Linear Mixed Model
hTEV	heteroscedastic Tree Extreme Value

1 Introduction

Household travel surveys are fundamental for the understanding of the socio-economic factors underlying travel behavior. These surveys provide basic information on household and individual level characteristics, and activity-travel information of household members (Goulias, 2013). In many regions around the world, travel survey data are used almost entirely for their richness, depicting fluctuations in travel patterns and household socio-demographics by calculating basic statistical measures such as trip activity means and standard deviations (Ortuzar, et al., 2010). Other regions collect such data for the training and development of sophisticated policy-oriented travel demand models.

The first generation of household travel surveys in North America can be dated back to the early 1960s, where transportation planning officials in the United States decided to assemble Origin-Destination (OD) data based on a relatively coarse zoning system (Cambridge Systematics Inc., 1996). After the introduction of the trip diary in the 1970s, a wide scale adoption ensued with transportation planning authorities collecting information on household members socio-demographics and trip behavior. The introduction of the trip diary prompted the first acceptable procedure for conducting large-scale household travel surveys (Harvey, 2003). Almost all of these surveys were cross-sectional in nature. A cross-sectional survey is defined as a survey executed at a point in time and conducted on a one-off basis. Large regional household travel surveys, while typically conducted over weeks or months, are still considered cross-sectional, as the data are pooled to represent a “typical day” (Verreault & Morency, 2011).

Practitioners have always had issues with these surveys, especially with data quality and low response rates. There have been numerous efforts to improve household surveys, most of which (whether it be the trip diary or the activity diary) are concerned with reducing missing/omitted trip information and response burdens. Further, the fact that the data collected from a cross-sectional survey attempts to mirror a typical day hinders the ability of transportation planners from capturing temporal trends of travel behavior. That is, the static nature of the collected data prevents the investigation of changes in travel behavior over time. Another major dilemma pertained to the design of household travel surveys is the issue of sample size. Transportation planning authorities have often struggled, in the light of political considerations and budget constraints, to identify the required sample size sufficient to depict travel behavior and generate statistically adequate OD matrices.

1.1 The Issue of Sample Size

The statistical methods for estimating sample size for a survey when a particular variable is of interest are well established. Examples provided by (Kish, 1965; NCHRP, 2008) illustrate the systematic approach of obtaining sample size estimates for both continuous and discrete variables. The question that is yet to be answered is: *what is the most appropriate sample size and, consequently, sampling rate for a multi-objective household travel survey for a large urban area*? In other words, what sample size is required to significantly capture the many variables of interest in a household travel survey (e.g. household size, income, trip rates per household, etc.), while constructing a statistically adequate OD matrix.

The sample size of the 2011 Transportation Tomorrow Survey (TTS) of the Greater Toronto and Hamilton Area (GTHA) was determined to be approximately 159,157 households, which is equivalent to 5% of the overall GTHA population (DMG, 2013). Such a sampling rate is in line with that of large household travel surveys of around the world during the 1960s and 1970s (Smith, 1979). However, sampling rates have declined in the 1980s in many parts of the world, with the exception of Canadian municipalities[1], to below 1%. As a result, many municipalities in the United States for example have complained of low county-to-county trip counts and inaccurately low transit modal shares (NCHRP, 2008). This decline in sample size is largely attributed to a study executed by Smith (1979). Smith proposed that only a small sample size of approximately 1200 households is necessary to calibrate travel demand models. However, he also admitted that such a small sample size hinders the ability of transportation authorities to depict travel patterns and construct statistically adequate OD matrices. His argument was that the construction of such matrices at a disaggregate level is difficult to achieve with a cost effective sample size.

[1] See chapter 2

In light of the discussion above, sample size determination for household travel surveys has proven to be a controversial element in the urban planning process, as statistical considerations are often dominated by cost and political considerations (NCHRP, 2008). In this thesis, an attempt is made to propose a methodology that can assist transportation authorities to determine the sample size necessary to calibrate travel demand models and to construct reliable OD matrices, albeit at a relatively aggregate scale. While recognizing that the exact control of sample size is impossible in most situations (Kish, 1965), a theoretically justified lower limit may be achieved. The investigation is inspired by the redesign of the TTS, North America's largest household travel survey. Sample size considerations are then extended to the context continuous surveys.

1.2 Continuous Surveys: A Viable Alternative

Almost all travel survey researchers recommend a combination of data sources to replace large cross-sectional travel surveys. These data sources include small sample panel surveys with the application of GPS/smartphone, continuous surveys as opposed to simple cross-sectional surveys, etc. A panel or longitudinal survey is one where households (or individuals) are repeatedly sampled, preferably over a long period of time. On the other hand, a continuous survey is an ongoing repeated cross-sectional survey where sampling time intervals are in very close proximity (usually a day). In other words, new households are sampled every day with no household sampled twice.

One of the key arguments for replacing large household cross-sectional surveys by continuous surveys is the dynamic nature of the data. In essence, the continuous element of an ongoing survey may be leveraged for time series analysis. This is in contrast to cross-sectional surveys as it enables transportation officials to depict the temporal nature of travel behavior. Nevertheless, no empirical evidence can be found in the transportation literature using continuous data to support that claim. Another advantage of continuous surveys over large sample cross-sectional surveys is the lower sample size requirement. If the rolling average of aggregate travel information is considered (e.g. trip rates, modal share, etc.), a smaller continuous travel survey can provide data of similar statistical strengths to that of a once-in-a-while large cross-sectional survey (Ortuzar, et al., 2010). Further, the capital overhead required to conduct a household survey is divided over an elongated period of time, and is therefore easier to budget as an annual expenditure (Stopher & Greaves, 2007).

Some regions in Canada (e.g. Calgary, Montreal) have been testing the feasibility of replacing large sample household travel surveys by continuous surveys. The Montreal metropolitan agency has been conducting large cross-sectional household travel surveys every 5 years since the 1970s (Habib & El-Assi, 2015). The surveys are relatively large with a sampling rate of approximately 5%. In 2009, right after Montreal's most recent OD survey, the agency launched an experimental continuous survey (Tremblay, 2014). The survey ended at the end of the year 2012, a few months before the start of Montreal's next major OD survey in 2013.

Like other metropolitan areas, Montreal has been facing increasing challenges in the conduct of its typical household travel survey in relation to declining response rates, incompleteness of sampling frame, inability to monitor changes, etc (Tremblay, 2014). Montreal relies on its large-scale household travel surveys to support decision making regarding transportation investments (subway extension for instance) and being able to measure the changes in behaviors after important changes in transportation supply is of great importance. It is the aim of the region to build on lessons learned from previous household travel survey and incorporate the necessary changes pertained to sampling frame and survey design to improve data quality and answer previously neglected questions such as seasonality of behavior.

1.3 Research Objective

The objectives of this thesis are as follows:

1. Investigate the issue of sample size for a large household travel survey for both cross-sectional and continuous surveys.

2. Propose a methodology that can be used to update OD matrices leveraging continuous waves of data, such as in a typical continuous survey, while defining an acceptable lower limit for sample size for a large household travel survey such as the TTS.

3. Examine the state of practice of continuous surveys around the world, and compare the practice of continuous surveys to its cross-sectional counterpart.

4. Investigate the capacity of continuous household travel surveys in capturing the temporal variation in travel demand. The analysis is to be conducted on the individual, household, trip, modal and different spatial levels.

1.4 Thesis Outline

This thesis consists of 7 chapters. Chapter 2 sheds light on the issue of sample size for cross-sectional and continuous household travel surveys. The chapter also explores the methodologies used to construct statistically reliable OD matrices, essential for sample size determination. Chapter 3 focuses on the state of practice in continuous household travel surveys around the world. Chapter 4 introduces the multilevel/mixed effects econometric framework, adopted to conduct analysis using continuous survey data. Specifically, the econometric framework is to be used to investigate the capacity of continuous data to depict the temporal variation in travel behavior. Chapter 5 provides a detailed description of the Montreal Continuous Survey, the dataset to be used for the modelling exercise, followed by how the dataset was prepared and cleaned. Chapter 6 discusses the result of the modelling exercise for a continuous outcome of travel behavior and identifies the extent of the capacity of continuous household travel surveys in capturing temporal trends in travel behavior. This chapter also extends the modelling exercise conducted for discrete outcomes. Finally, chapter 7 concludes with a summary of the main outcomes of this thesis and directions for future work.

2 The Issue of Sample Size

2.1 Literature Review

The predicament of determining sample size for large household travel surveys has always been a contentious topic for researchers and transportation planners alike. It has been established that the determination of the sample size for the estimation of population parameters depends on three main factors (Kish, 1965; Richardson, et al., 1995):

a) The variability of population parameters to be measured
b) The degree of precision required for each parameter estimate
c) The population size

Where factor b) is constituted of the allowable tolerance of errors in measurement, and the desired confidence limit on the estimates from the sample. Nevertheless, it is difficult to extend this estimation technique for a large household travel survey with numerous parameters of interest (e.g. trip rates, trip distance, household size, number of vehicles owned, gender, occupation status, age, etc.).

In the early days of household travel survey design, the standard sampling rate, defined as the sample size divided by a population, was anywhere between 5% to 10% of population size (Smith, 1979). However, Smith (1979) argued that if the main purpose of a household travel survey is to simply develop travel demand models rather than depicting travel patterns using a rich OD matrix, the use of a substantive sample size for the design of household travel surveys conducted at a fixed time interval (usually every 5 or 10 years) is unnecessary. Considering that stable estimates of key variables from previously designed surveys are available, a small sample size may be sufficient to update the different components of a travel demand model. An empirical investigation proposed by Smith deduced that with proper estimates of mean and variances of key variables from a large scale survey, a sample of fewer than 1200 households may be enough for updating a cross-classification model of trip generation as a function of automobile ownership and income. However, if trip rates per jurisdiction (i.e. zone/county) of a multi-jurisdiction study area are of concern, a sample of 1100 household per jurisdiction is necessary.

Smith proposed a systematic procedure for estimating the sample size of a small scale household travel survey necessary for developing the various travel demand modelling components. The procedure was proposed for simple random sampling. He identified trip distribution as the critical element that drives up the sample size requirement of household travel surveys. Smith proved that a 4% sample is necessary to achieve a 90% confidence interval with a 25% standard error for trip interchanges between OD pairs with less than 1100 trips in between. This has led latter researchers, such as Ortuzar, to suggest the use of secondary data sources (e.g. cordon counts, etc.) to create and update OD matrices as opposed to conducting a household travel survey of a relatively large sample size (Ortuzar, et al., 2010).

Stopher (1982) extended the proposed procedure of Smith for stratified random sampling. His sample size calculation also considered that accurate estimates of mean and variance of key variables would be available. Nonetheless, the availability of such input statistics for stratified geographic areas is difficult to assume. For example, Kollo and Purvis (1984) collected household travel survey data over a 20-year period and found that trip rates only remain stable over time if aggregated. In other words, disaggregation of trip rates by purpose causes instability over time.

The next remarkable document that has, in part, focused on household travel survey sample size determination is the Travel Survey Manual (1996) prepared by Cambridge Systematics for the United States Department of Transportation. The report states that the determination of sample sizes for household travel surveys is the result of a trade-off between budgetary constraints and sample size requirements for accurate representation of the sampled population. It also reports that the exhaustive objectives of household travel surveys inhibit the optimization of sample size estimation (i.e. too many important variables). Further, the document recommends that one out of every hundred households (1% of the population) for large urban areas and one of every ten households (10%) for small suburban areas should be the minimum sample size for household travel surveys. The report capitalizes on the fact that the drop of household travel surveys' sample sizes from over 4% to less than 1% of households happened during the late 1980s without necessarily affecting the accuracy of demand modelling. This is another evidence of the impact of the research conducted by Smith (1979) and subsequent researchers. On the other hand, it also recognizes the importance of large sample sizes for increasing the reliability of sample statistics. It provides a step-by-step procedure for sample size estimation of various types of target variables, and for different sampling procedures. However, it provides no definite guideline for sample size determination for a generalized multi-objective household travel survey that can be used by different planning agencies for various purposes.

Greaves and Stopher (2000) highlighted the importance of large household travel surveys while recognizing their high cost. The authors stated that large sample sizes are being increasingly demanded for developing advanced disaggregate travel demand models. They proposed a simulation technique to generate synthetic household travel surveys in the absence of large sample household travel surveys. The simulation takes the conditional distributions from the National Personal Travel Survey (NPTS) and Public Use Microdata Sample (PUMS) to generate an artificial sample. The PUMS is a 5% sampling rate and so is considered a reliable data source. Pointer et al (2004) also used the same procedure to generate a synthetic household travel survey data for Sydney. They used the Sydney household travel survey, a relatively small continuous survey of 3000 households per year. They pointed out that, though estimating a travel demand model for a region may not need a large household travel survey, portraying an accurate picture of the spatial distribution of travel demand within the region requires a large sample size.

Ampt and Ortuzar (2004) presented a comprehensive discussion on the sample size requirements of household travel surveys. The authors investigated the sample size of OD trips from a group of only 34 zones in Santiago by using data from the 1991 Santiago O-D survey. They re-confirm that they would need at least a 4% sample to achieve a 90% confidence and 25% standard error for the number of trips between OD pairs if they were to conform to Smith's (1979) proposition. A 4% sample size was identified as too large considering trip distribution as a meagre objective of the overall household travel survey. They also proposed an alternative heuristic algorithm based on stratified random sampling of selected socio-economic variables to calculate sample size for selected parameters of interest. However, they recognized the fact that actual sample size requirements may be very large if geographic distributions of key variables (e.g. zonal or sub-regional estimates of household car ownership) are of concern. The authors proposed that large metropolitan areas should implement small sample continuous household travel surveys with once-in-a-while large sample cross-sectional surveys. Stopher and Greaves (2007) further proved that if a continuous panel survey is to be the method of choice, sample size requirements reduce drastically. Moreover, the combination of one of the aforementioned approaches with the use of GPS devices, and weeklong surveys instead of a one-day survey is capable of further reducing sample size requirements for household travel surveys (Stopher, et al., 2007).

In addition, Stopher et al (2008) showed that even with increasing response burden and the possibility of attrition, a week-long household travel survey can be more efficient than a 24-hour travel survey as it demands a smaller sample size requirement. It also provides a rich dataset that can reflect the dynamics of travel behaviour. As an empirical anecdote, the authors proved that a 7 day GPS assisted household travel survey would require a sample size that is 35% less than that of a typical 1-day household travel survey. Similarly, Bolbol et al (2012) suggested a procedure for estimating sample size requirement for GPS-assisted household travel surveys. They suggest that the temporal variability of travel mode choices has to be carefully considered for sample size determination. Further, Goulias et al (2013) experimented with a week-long GPS assisted household travel survey as the core for their core-satellite approach of urban travel data collection. They recommend small yet detailed household travel surveys as the core, which should follow the form of week-long travel diaries of household members. However, the small sample has then to be complemented by a series of carefully designed satellite (synonymous to an augment survey) surveys targeting specific variables that are under or unrepresented in the core. Nevertheless, their proposal provides no guidelines on sample size requirements.

The NCHRP report (2008) stated that even strictly designed (statistically efficient) sample sizes may not be sufficient for serving many of the critical objectives. The 1990 Southern California household travel survey was presented as a case study. A statistically adequate sample size was estimated (3,500 to 5,000 households). However, the actual sample size was selected to be 15,000 households, partly due to political reasons. Interestingly, even with such a large sample size, the collected data were not adequate. Low transit modal shares proved to be a major problem, resulting in a small number of observed transit trips. The number of trips was not large enough to estimate a reasonable mode choice model.

In summary, it is evident that there is a lack of consensus on the appropriate guidelines for establishing sample sizes for household travel surveys. Although theoretically the sample size can be quite low, the actual sample sizes of urban household travel surveys vary widely.

Different trends are observed in different parts of the world. The following section presents a discussion on this.

2.2 Comparison of Recent Household Sampling Rates from Around the World

Table 2-1 presents a list of recent household travel surveys from the US, Canada, Australia, Europe and South America. The selection of this list is based on web-accessible information. Although it does not provide an exhaustive list of all household travel surveys around the world, it portrays the distinctive approaches in major cities/urban regions.

Table 2-1 Sample Sizes of Recent Household Travel Surveys Around the World

City/Region	Survey	Year	Sampling Rate
	Canada		
Calgary	Calgary Travel and Activity Survey[2]	2012	3.4% of households
Edmonton	Edmonton Household Travel Survey[3]	2005	2.6% of households
Greater Montreal Region	Greater Montreal Area Origin-Destination Survey[4]	2013	4.6% of households
Greater Toronto and Hamilton Area: GTHA	Transportation Tomorrow Survey: TTS[5]	2011-2012	5.0% of households

[2] http://wwwsptest.calgary.ca/Transportation/TP/Pages/Planning/Forecasting/Forecasting-surveys.aspx

[3] http://www.edmonton.ca/transportation/RoadsTraffic/2005_HTS_Region_Report_FINAL_Oct24_06.pdf

[4] https://www.amt.qc.ca/fr/a-propos/portrait-mobilite/enquetes-en-cours

[5] http://www.dmg.utoronto.ca/transportationtomorrowsurvey/

National Capital Region: NCR	NCR Origin-Destination Survey[6]	2011	5.0% of households
Saskatchewan	Saskatoon Household Travel Survey[7]	2013	3.0% of households
Vancouver	Metro Vancouver Regional Trip Diary Survey[8]	2011	2.2% of households
Winnipeg	Winnipeg Area Travel Survey[9]	2007	3.3% of households
		United States	
Atlanta Region	Regional Travel Survey[10]	2011	0.5% of households
Chicago Metropolitan Area	Regional Household Travel Inventory[11]	2007-2008	0.44% of households
Dallas Metropolitan Area	Household Travel Survey[12]	2008	0.24% of households
New York and New Jersey Metropolitan Area	Regional Household Travel Survey[12]	2010-2011	0.24% of households

[6] http://www.ncr-trans-rcn.ca/surveys/o-d-survey/o-d-survey-2011/

[7] https://www.saskatoon.ca/sites/default/files/documents/transportation-utilities/transportation/planning/Attachment3%20Technical%20Report%20HTS_FollowUp_report.pdf

[8] http://www.translink.ca/en/Plans-and-Projects/Transportation-Surveys.aspx

[9] http://transportation.speakupwinnipeg.com/WATS-Final-Report-July2007.pdf

[10] file:///C:/Users/khandker-admin/Downloads/tp_2011regionaltravelsurvey_030712.pdf

[11] http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/34910

[12] http://www.nymtc.org/project/surveys/survey2010_2011RTHS.html

Southeast Florida	Household Travel Survey[13]	2007-2008	0.11% of households
The State of California	California Household Travel Survey[14]	2010-2012	0.34% of households
Utah State	Household Travel Survey[15]	2012	1.0% of households
	Australia		
Adelaide	Travel Survey[17]	1999	1.4% of households
Brisbane	Travel Survey[16]	2009	1.3% of households
Canberra	Travel Survey[17]	1997	2.6% of households
Greater Melbourne Area	Victoria Integrated Survey of Travel and Activity[17]	2012	0.35% of households per year
Hobart	Travel Survey[17]	2008-2009	2.9% of households
Sydney Greater Metropolitan Area	Continuous Household Travel Survey[18]	2015	0.3% of households per year
	Europe		

[13] http://www.fsutmsonline.net/images/uploads/mtf-files/Southeast_Florida_Household_Travel_Survey_0205_2014.pdf

[14] http://www.dot.ca.gov/hq/tpp/offices/omsp/statewide_travel_analysis/files/CHTS_Final_Report_June_2013.pdf

[15] http://www.wfrc.org/new_wfrc/publications/Utah_FinalReport_130228.pdf

[16] (Stopher, et al., 2011)

[17] http://economicdevelopment.vic.gov.au/transport/research-and-data/vista

[18] http://www.bts.nsw.gov.au/Statistics/Household-Travel-Survey/default.aspx#top

France	National Transport and Travel Survey[19]	2007-2008	Less than 0.1% of households
Germany	Mobilitat in Deutschland (MiD)[20]	2008	Less than 0.1% of households
The Netherlands	Onderzoek Verplaatsingen in Nederland (OViN)[21]	2011	0.26% of households
Spain	Movilia[22]	2007	0.31% of households
Switzerland	Microcensus on Travel Behavior[23]	2010	0.67% of households
South America			
City of Rosario, Argentina	Household Travel Survey[24]	2002	3% of households
Greater Santiago Area	Origin-Destination Survey[25]	2012-2013	1% of households

It is evident from the table that Canadian regions and municipalities still favor the practice of large household travel surveys with sampling rates ranging from 2% to 5%. Almost all Canadian household travel surveys are predominantly telephone-based with some introducing a web-version of the telephone survey and small-scale GPS applications (Miller, et al., 2012).

[19] http://www.insee.fr/en/methodes/default.asp?page=sources/ope-enq-transports-deplac-2007.htm

[20] http://mobilitaet-in-deutschland.de/02_MiD2008/index.htm

[21] http://www.cbs.nl/nlnl/menu/informatie/deelnemersenquetes/personen-huishoudens/ ovin/doel/default.htm

[22] http://www.fomento.gob.es/mfom /lang_castellano/estadisticas_y_p ublicaciones/informacion_estadis tica/movilidad

[23] (Ohnmacht, et al., 2012);

[24] (Ampt & Ortuzar, 2004)

[25] http://datos.gob.cl/datasets/ver/31616

Vancouver had the smallest sampling rate of all Canadian cities (2.2%). The metro region has stated in the past that the objective of the survey is mainly for model calibration purposes. The 2008 Metro Vancouver report mentioned that, for obtaining detailed travel statistics such as trip rates and mode shares, a larger sampling rate will be required. Nonetheless, the magnitude of such a survey may be too large adding costs and complexity to the data collection process (Mustel Group & Halcrow, 2010).

On the other hand, almost all household travel surveys in the US have a sampling rate of less than 1%. However, US surveys are more dynamic in adopting advanced technology, e.g. GPS. The 2010-2011 New York and New Jersey regional household travel survey used a 10% sub-sample of households to collect a wearable GPS-based travel diary data. Even though the sample size remains small, the subsample was successful in accessing socio-economic groups that otherwise would not have participated in the survey (Stopher & Greaves, 2007). Further, the GPS subsample allowed the New York Metropolitan Transport Council along with the North Jersey Transportation Planning Authority to calculate statistically reliable trip rates that would have otherwise been more difficult to determine using a relatively small sample size. Still, the survey report recognizes the fact that this sample size might be too thin for various travel segments (NYMTC & NJTPA, 2014). The 2010-2012 California household travel survey employed a 12% sub-sample for a wearable GPS-based travel survey (Kunzmann, 2013). The biggest travel survey in the US is the National Household Travel Survey (NHTS) with a sampling rate of approximately 1%. However, in many cases, such data alone are not considered sufficient for demand modelling and evidence-based transportation planning exercises. The Southeast Florida Household Travel Survey, for example, conveyed difficulty in determining detailed observed travel patterns at the county and/or sub-county levels due to the small sample size (SEFTC, 2014). Other difficulties reported include the underrepresentation of certain socio-demographic groups.

Australian cities have been implementing both cross-sectional and continuous travel survey approaches (Ortuzar, et al., 2010). Indeed, many regions around the world are experimenting with continuous surveys as a viable substitute for the traditional cross-sectional survey (see chapter 3). In either case, household travel survey sample size determination is an important concern. Even for continuous surveys, it is recommended to pool the ongoing surveys in large intervals (3 or 5 years) to form a large pseudo cross-sectional survey (Ampt & Ortuzar, 2004). Nevertheless, due to the lack of proper statistics, it is difficult to approximate the sample sizes of Australian surveys. However, it is clear that Australian surveys favor small sample sizes (Stopher, et al., 2011). Nevertheless, Stopher et al (2011) have highlighted the lack of consistency among these surveys thus limiting the potential of fusing the numerous datasets into one large survey, which the authors listed as an objective of various Australian planning agencies. It is also worth noting that Australia is home to one of the oldest running continuous surveys, the Sydney Household Travel Survey (Ampt & Ortuzar, 2004). Prior to 1997, the Greater Sydney Area used to conduct large-scale cross-sectional surveys every 10 years. Since then, the area has been running a continuous survey. The data are pooled every 3 years, where the total sample size equals that of the pre-1997 cross-sectional survey. Other areas, such as the Central Melbourne area, use a cross-sectional household travel survey. The region uses both a land line based interview (55% of total sample) and a roadside intercept approach (45% of total sample) for data collection.

The European continent has the most consistent national household travel surveys. Bonnel et al. (2007) stated that national household travel surveys in Europe vary widely in terms of sample sizes. Further, the authors report that the sample size determination is not correlated with the size or the characteristics of the countries respected populations. In South America, Chile, specifically the city of Santiago, has been a global leader in travel surveys. The latest Santiago household travel survey is of around 1% of the total household population in the region. Chile also has been experimenting with various approaches e.g. continuous surveys, use of GPS technology and panel surveys (Ortuzar, et al., 2010).

Overall, it is clear that there is no consensus on the selection of sample sizes for household travel surveys. There are, however, recommendations on moving to continuous surveys instead of one-off surveys, but the issue of sample size is rarely tackled. Lack of proper data due to small sample sizes of household travel surveys in the US has presented an issue for many researchers due to their inability to investigate detailed disaggregate (at a zonal or sub-regional level) travel behaviour. Some regions in the US have put forward the claim that small sample sizes prevent the observation of detailed travel patterns at the county or sub-county levels, and under represent certain segments of the population (SEFTC, 2014). That said, even large cross-sectional household travel surveys may not be able to accurately capture all the socio-demographics of a population in the targeted survey area. The next section (2.3) investigates the representativeness of the GTHA's TTS - one of the largest household cross-sectional surveys in North America. After that, the minimum required sampling rate to construct statistically adequate OD matrices is investigated.

2.3 An Empirical Investigation on the Representativeness of the Transportation Tomorrow Survey

The Transportation Tomorrow Survey in the GTHA is one of the largest (5%) and most regularly conducted (every 5 years since 1986) household travel survey in North America (DMG, 2016). The TTS study area is composed of 30 municipalities in addition to City of Toronto's 16 planning districts; the City of Toronto is the largest municipality in the GTHA. The TTS has also been extended to include several smaller municipalities outside the borders of the GTHA. The 2011-2012 TTS survey data were used to investigate the TTS representativeness of the various socio-economic characteristics of its population. Figure 2-1 presents the aggregate region-to-region peak-period trip matrix of the study area (DMG, 2016).

Within the GTHA, the City of Toronto is the largest urban area with an established Central Business District (CBD). Its neighboring regions of Halton, York, Peel, and Durham feature independent municipalities. These regions function more or less as suburbs for Toronto. Almost all Origin-Destination pairs of the City of Toronto, Peel Region and Halton Region have more than 1100 peak period trips between them. Hence, based on the findings of Smith (1979), a 4% sample for these areas should be sufficient to adequately model trip behavior. However, in the case of the City of Hamilton and the Region of Durham and York, the majority of OD pairs have less than 1100 trips in the peak period. If we consider peak period transit trips, then the numbers are likely to be even worse.

Moreover, in order to further investigate how well the 5% TTS sample represents the whole population, the Root Mean Square Error (RMSE %) method was used to estimate the error/bias between the 2011 TTS and the 2011 census. Kish (1965), as well as NCHRP (2008), recommended this method to estimate error/bias in surveys. It is important to note that bias could be the result of sampling, in addition to measurement error, coverage error, and non-response.

From/To	City of Toronto	Region of Durham	Region of York	Region of Peel	Region of Halton	City of Hamilton	Region of Niagra	Region of Waterloo	City of Guelph	County of Wellington	Town of Orangeville	City of Barrie	County of Simcoe	City of Kawartha Lakes	City of Peterborough	County of Peterborough	City of Orillia	County of Dufferin	City of Brantford	County of Brant	Region Totals
City of Toronto	510,000	7,300	62,600	47,900	5,000	900	400	600	200	.	.	300	400	.	100	.	.	.	100	.	635,800
Region of Durham	51,800	72,800	15,900	3,200	300	100	.	200	.	.	.	.	100	400	800	100	.	.	.	.	145,700
Region of York	123,600	4,300	127,800	20,500	1,600	300	100	400	100	.	.	700	1,800	100	100	.	100	.	.	.	281,500
Region of Peel	92,600	700	18,200	188,600	15,900	1,400	500	1,200	600	200	600	100	700	.	.	.	100	200	100	.	321,700
Region of Halton	28,000	200	2,800	37,700	52,300	7,900	800	2,000	700	400	.	100	100	.	.	.	.	.	200	100	133,300
City of Hamilton	4,600	100	600	6,100	21,000	72,700	2,600	2,000	500	.	.	.	.	.	.	.	.	.	1,600	400	112,200
Region of Niagra	1,300	100	100	1,000	3,800	6,300	75,900	100	100	.	.	.	.	.	.	.	.	.	100	.	88,800
Region of Waterloo	1,300	100	200	3,100	1,800	1,200	100	104,400	7,600	1,300	.	.	100	.	.	.	.	.	800	400	122,400
City of Guelph	800	.	200	1,400	1,500	400	100	3,400	21,000	1,700	100	.	.	.	.	.	.	.	.	.	30,600
County of Wellington	400	.	200	1,900	1,100	100	.	2,100	4,200	3,600	300	.	.	.	.	.	.	.	.	.	13,900
Town of Orangeville	400	.	400	3,400	200	.	.	.	100	100	2,100	.	100	.	.	.	.	600	.	.	7,400
City of Barrie	1,600	100	2,800	1,000	100	.	.	.	.	100	.	17,500	5,400	.	.	.	600	.	.	.	29,200
County of Simcoe	4,000	400	8,300	3,000	200	100	.	100	.	100	300	10,500	29,300	.	.	.	3,600	300	.	.	60,200
City of Kawartha Lakes	300	2,600	500	100	.	.	.	.	.	.	.	100	200	8,600	1,500	300	100	.	.	.	14,300
City of Peterborough	100	700	.	.	.	.	.	.	.	.	.	.	.	500	12,400	2,100	.	.	.	.	15,800
County of Peterborough	100	500	.	.	.	.	.	.	.	.	.	.	.	400	5,700	2,000	.	.	.	.	8,700
City of Orillia	.	.	100	.	.	.	.	.	.	.	.	500	1,200	.	.	.	3,400	.	.	.	5,200
County of Dufferin	300	.	200	2,000	200	.	.	100	100	200	1,400	.	400	.	.	.	.	1,700	.	.	6,600
City of Brantford	200	.	100	300	600	2,100	100	1,200	200	.	.	.	.	.	.	.	.	.	1,200	2,400	8,400
County of Brant	100	.	.	100	300	900	.	1,700	100	.	.	.	.	.	.	.	.	.	2,800	2,400	8,400
Region Totals	821,500	89,900	241,000	321,300	105,900	94,400	80,600	119,500	35,500	7,700	4,800	29,800	39,800	10,000	20,600	4,500	7,900	2,800	6,900	5,700	2,050,100

Figure 2-1 Peak Period Trip Matrix of 2011-2012 TTS

$$Percent\ RMSE = \sqrt{\frac{1}{n_i}\sum_{i}^{n_i}\frac{1}{n_{ji}}\sum_{j}^{n_{ji}}\left(\frac{r_{ij}-s_{ij}}{r_{ij}}\right)^2} \times 100 \qquad (1)$$

Where:

n_i is the number of variables
n_{ji} is the number of category j in variable i
r_{ij} is the reference value (in census) of variable i in category j
s_{ij} is the sample value of variable i in category j

As it is clear in the equation, the higher the error for a particular variable, the higher is its representation bias of the whole population. We selected the socio-economic and household specific variables that are common between 2011 TTS and the 2011 census, considering census data as a reference. The following variables were used to estimate the RMSE of 2011 TTS data:

- Number of males
- Number of females
- Number of employed people
- Use of modes:
  - Private car driver; Private car passenger; Transit users; Pedestrians; Bicycle users and Other mode users
- Age groups:
  - Under 14 years; 14+, up to 24 years; 24+, up to 44 years; 44+, up to 64 years and 64+ years
- Household sizes:
  - 1 person; 2 persons; 3 persons; 4 to 5 persons and 6 or more persons

Figure 2-2 presents the results of 6 cities in the GTHA. The cities are Toronto, Hamilton, Mississauga (Peel Region), Brampton (Peel Region), Oshawa (Durham Region), and Markham (York Region). The majority of the RMSE is below 20% for both 2011-2012 and 1991 TTS. In other words, TTS data represents its target population with an 80% accuracy margin. Part of the 20% error margin is germane to its sampling frame (landline phone directory), which cannot be eliminated by simply increasing sample size. Results show that non-motorized modes and transit modal shares have a higher error percentage than private automobile use. Error dispersion is higher in 1991 for cities other than Toronto. This may be due the adoption of a differential sampling strategy in 1991. Since the 1991 census didn’t capture modal share, it was not possible to assess the accuracy of the 1991 TTS data. Nevertheless, it seems that a 5% sample can produce data representing the target population with an 80% plus level of accuracy.

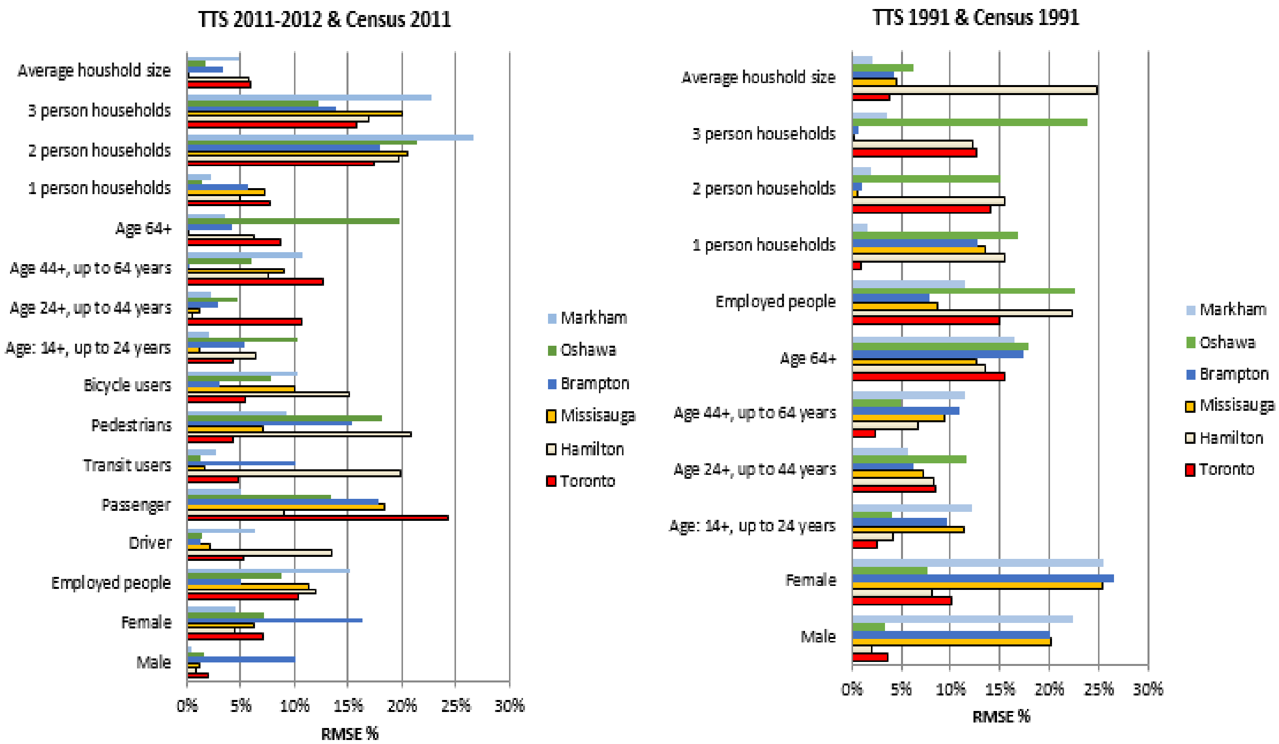

Figure 2-2 RMSE of Selected Areas in the GTHA

It is imperative to note, however, that the RMSE estimation of the cities and variables is dependent on variable availability, and the commonality of spatial boundaries in both TTS data and corresponding census data (StatsCan, 2011). Further, the census mode to work question is not identical to that of the TTS, and the 2011 long form census itself can’t be perceived as an identical mirror of the population. It is also important to note that the 2011 TTS featured a consistent sampling rate of approximately 5% across all regions. On the other hand, the 1991 TTS adopted a differential sampling rate distinguishing between “high growth” and “low growth” areas where the former was sampled at a 4.5% rate and the latter at 0.5%. The mean sampling rate of the 1991 TTS was 1.4% (DMG, 2016).

The empirical exercise discussed investigates the representativeness of a household travel survey as compared to the census (or any other proxy for the true population). Nevertheless, the representativeness of the sample does not equate to the suitability of using the data to construct statistically adequate OD matrices to depict travel patterns. The following section tackles this issue, and proposes a lower limit sampling rate for the TTS; treated as a case study.

2.4 An Empirical Investigation on the Sample Size Requirement for Trip Distribution

It has been generally accepted that zone-to-zone trip matrices are difficult to construct with an appropriate level of accuracy using trips sampled via a household travel survey (Cambridge Systematics Inc., 1996). Cools et. al (2010) conducted an assessment of the quality of Origin-Destination trip matrices derived from activity surveys using a Monte Carlo experiment set up to estimate the precision of these matrices at various sampling rates. The authors calculated the Mean Absolute Percentage Error (MAPE) of OD matrices for different sampling rates generated using the Belgium national census. They concluded that only when half of the population is sampled can an acceptable OD matrix be obtained at the provincial level, a sampling rate too large to be undertaken by any government authority. Nevertheless, the study also noted that an OD matrix for peak period commuter-only travel reproduced from a sampling rate of only 1% has a MAPE of 19%. Therefore, it is possible to construct statistically adequate OD matrices if the level of disaggregation is not too thin.

As previously discussed, one of the most prominent pieces of work that relates OD trip matrices to sample size estimation is a graph proposed by Smith (1979). The graph represents the number of trips expected for a given interchange – from one spatial unit to another such as zone-to-zone or region-to-region. The rate, however, is based on randomly selected trips rather than randomly selected households. Smith argues that OD trip matrices are simply not feasible because a high sampling rate is required to produce acceptable trip estimates. While not necessarily incorrect, this does not always have to be the case.

Smith correlated the to-be-determined sampling rate to the total number of trips between origin and destination. Nevertheless, he admitted that relationship varied depending on the heteroscedasticity of the population, determined by the coefficient of variation of total trips. The coefficient of variation (CV) is a standardized statistical measure of dispersion of a frequency or probability distribution, calculated by dividing the standard deviation by the mean (Searls, 1964).

Smith assumed a constant coefficient of variation of 1 when constructing his graph[26]. However, travel behavior is not constrained by a specific distribution, rather it is best represented by a spectrum indicating potential homogeneous and heterogeneous travel patterns. Therefore, in an attempt to better understand the sample size requirements to construct OD matrices, a portion of the graph was recreated using a range of CVs from 0.5 to 1.5, with a 0.25 increment.

The Y-axis of the graph (Figure 2-1) represents the sample size (here, the number of trips between an OD pair) to be surveyed divided by the trip totals (i.e. the sampling rate). The sample size is bounded by a confidence interval. It is calculated using the following formula proposed by Smith (1979):

$$\text{Sample Size} = CV^2 * \frac{Z^2}{E^2} \qquad (2)$$

Where:

CV is the coefficient of variation of total trips
Z is the level of confidence
E is the acceptable level of accuracy expressed as a proportion

Moreover, the number of trips to be captured will vary depending on the coefficient of variation, thus the different colors. A confidence interval of both 90% and 95% for trip totals between OD pairs, along with a level of accuracy of 25%, were assumed. The X-axis is simply a series of hypothetical trip totals between OD pairs. A logarithmic scale is assumed for both the Y and X-axis.

[26] Smith (1979) does not explicitly state that a CV of 1 was used to construct the graph. Different points were selected from the graph to reverse calculate the CV, as the sampling rate, population (number of trips), confidence interval and level of accuracy were all provided.

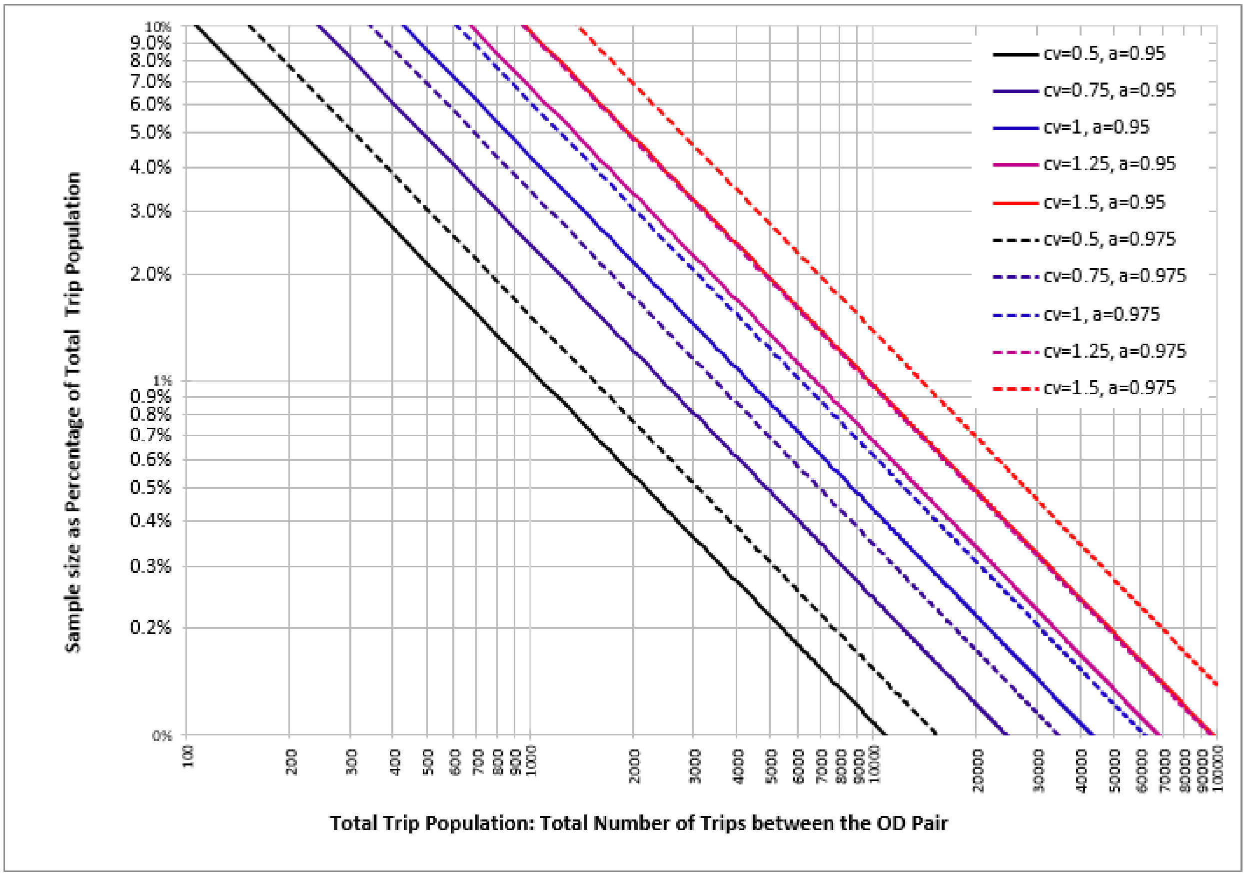

Figure 2-3 Sample Rates for Trip Distribution Based on Trip Counts and CV

The center blue line in Figure 2-3 is the equivalent of the left-most solid line in Smith's graph. As can be observed in Figure 2-3, as the CV decreases, the sample size requirements decrease accordingly and vice versa. Similarly, as the confidence interval increases from 90% to 95%, the required sampling rate also increases. Referring back to Figure 2-3, the coefficient of variation calculated for the trip cells between Hamilton and the City of Toronto (i.e. the GTHA) is approximately 0.5. The plot shows that for a CV of 0.5 and OD pairs with lower than 1000 trips, a sampling rate of approximately 1% is required. Further, although some trip cell values are less than 1000, many are in the order of 10,000. Thus, a 1% sampling rate may not be even necessary for such a spatially aggregated OD matrix.

Cities that exhibit homogeneous travel behavior (e.g. auto-captive population) can have a similar CV, such as that reported by Pearson and others (Cambridge Systematics Inc., 1996)[27]. On the other hand, a multi-modal region with a number of residential and employment hubs like the City of Toronto will probably have a larger CV, which will result in a larger sampling rate requirement. Moreover, further disaggregation (by mode, peak and off-peak travel periods and trip purpose or spatial units) will require even larger sampling requirements, as the number of trips conducted from each origin to each destination will likely be smaller.

To summarize this section, a 1% sampling rate has been identified as the minimum rate to depict travel patterns on a regional level for an area similar to the GTHA. Such a sampling rate equates to approximately 10,000 households. That said, continuous surveys may offer a more feasible alternative as OD matrices can be updated with continuous waves of data, leading to a more precise depiction of trip distribution while reducing sample size requirements (Ortuzar, et al., 2010). Section 2.5 investigates trip distribution in the context of continuous surveys and provides a simple methodology for updating OD matrices.

2.5 Trip Distribution in the Context of Continuous Surveys

The goal of constructing statistically adequate OD matrices lies at the heart of large household travel surveys. Consequently, the ability to reproduce OD matrices using continuous data with a reduced annual sample size is imperative for the consideration of a potential transition to a continuous survey approach. However, no published research has been found to provide a practical solution or approach to this issue. Given this, continuous or not, most household travel surveys outside Canada utilize a relatively small sample size (usually less than 1%). Transportation agencies have adopted other means to generate OD matrices, such as simulation or the use of data from highway loop detectors (Ampt & Ortuzar, 2004). That said, a smaller sample size of 1%, as is used in the Montreal continuous survey (1% per year) can possibly still reproduce a statistically adequate OD matrix with an absolute mean percentage error less than 20% for peak period commuters (Cools, et al., 2010).

[27] Pearson reported in 1974 coefficient of variations of 0.53 for home-based work trip and 0.58 for home-based non-work trips.

One approach is to simply produce OD matrices from the fall period of yearly continuous data. The fall is selected as it represents the season with the least number of vacations and exhibits a relatively moderate climate. Therefore, the fall period gives the modeller the best approximation of travel behavior on a "typical" weekday (Meyer & Miller, 2001). To resolve the issue of small sample size, the OD matrices over a predetermined period can be combined and updated. For example, the regional OD matrix of each year can be compared to the highway traffic counts to calculate the MAPE. A confidence factor can then be assigned to each O-D matrix, where the sum of all values equals to 1. Next, the matrices can be combined to generate a statistically adequate matrix. The following steps provide an illustration of how to construct this matrix for a five-year period. The period is determined by how frequent the transportation authority decides to execute a full model run. That is, if a full model run is executed every three years instead of five, then a three-year period OD matrix should be constructed.

- Construct the OD matrix for each year of continuous data using the fall period only
- Calculate the MAPE of each OD matrix (for every year)

$$MAPE_{ij} = \frac{\sum_i \sum_j APE_{ij}}{N} \qquad (3)$$

$$APE_{ij} = \left| \frac{A_{ij} - E_{ij}}{A_{ij}} \right| x100 \qquad (4)$$

Where:

A_{ij} = population count for the morning commute from origin i to destination j
E_{ij} = expanded sample count for the morning commute from origin i to destination j
N = total number of OD cells

After constructing the OD matrices for each year, and calculating the MAPE of each matrix, the following steps ensue:

- Sum up the error values to get a total "ε"
- Divide the error value ε_i for each year *i* by the total error value ε, such that $\sum_{i=1}^{n} \varepsilon_i{}' = 1$
- Adjust the OD matrices trip counts by multiplying the yearly error values by their respective OD matrices
- Sum up all the OD matrices over a 5-year period to construct an OD matrix similar to that of a 5% cross-sectional survey

$$\sum_i^n (\varepsilon_i' * \ OD_i) = \ OD \ over \ a \ 5 \ year \ period \qquad (5)$$

The suggested method above has one major flaw; the true OD matrix is assumed to be known. While this may be the case in some countries, such as Belgium, where work-and-school travel information is captured by the micro-census (Cools, et al., 2010), it is not the case in Canada. Alternatively, the population count for the morning commute can be obtained using loop detectors on highways or other surveillance technologies. Nevertheless, converting loop detector counts to OD matrices poses its own set of problems, as documented in the literature (Cascetta & Nguyen, 1988; Yang, et al., 1992).

In an effort to reproduce OD matrices from continuous surveys, a Bayesian estimation method for updating OD matrices using continuous waves of data is proposed. The Bayesian approach, as evident in the transportation literature, has been used to construct OD matrices from household travel surveys (Perrakis, et al., 2012), and to update OD matrices and intersection counts from link traffic flows (Castillo, et al., 2008; Maher, 1983). Indeed, it is possible to extend the use of Bayesian estimation to updating old OD matrices using new ones constructed from continuous waves of data. The following section provides a brief explanation of Bayes theory in the context of continuous data. The proposed methodology follows.

2.5.1 Background on Bayesian Updating

The Bayesian tradition poses a powerful set of procedures for the updating and estimation of OD matrices. Assuming a multivariate distribution over the rows (or columns) of an OD matrix at year *t*, it allows the parameters (mean and variance) of the models to be updated with the infusion of new 'evidence', such as a new OD matrix from year t_{+1}. Thus, Bayesian estimation provides an alternative for classical estimation methods. Since the OD matrix can be directly inferred from year *t* and t_{+1}, the modeller can easily calculate the mean, variance-covariance matrix or any other parameter θ of the assumed distribution over the rows or columns of the matrix.

Under Bayesian analysis, the parameters follow a probability distribution that indicates all possible values that the parameters can take. These values are represented by a density on θ called the prior distribution (denoted as $k(\theta)$) (Train, 2009). As the continuous survey rolls, more data are being collected. This data can be used to alter the prior parameter estimates by drawing a new density on θ, called the posterior distribution. The posterior distribution is labelled $K(\theta|X)$, where X represents a row or column vector with a set N of population counts in the OD matrix, aggregated over a specific time period.

Bayes rule establishes the relationship described above between the prior and posterior distribution. Formally, the probability of observing the data X is:

$$L(X|\theta) = \prod_{n=1}^{N} P(x_n|\theta) \qquad (6)$$

In essence, $L(X|\theta)$ represents the likelihood function of the observed data, and $P(x_n|\theta)$ is the behavioral model that relates the parameters and explanatory variables to the outcome (Train, 2009). Using Bayes rule, the posterior may be calculated:

$$K(\theta|X) = \frac{L(X|\theta)k(\theta)}{L(X)} \qquad (7)$$

Where $L(X)$ is the marginal probability of X, marginal over θ:

$$L(X) = \int L(X|\theta)k(\theta)d\theta \qquad (8)$$

A more succinct representation of Bayesian estimation is:

$$K(\theta|X) \propto L(X|\theta)k(\theta) \qquad (9)$$

That is, the posterior distribution is proportional to the prior distribution multiplied by the likelihood function (Train, 2009). The mean of the posterior distribution can be obtained via the following equation:

$$\bar{\theta} = \int \theta K(\theta|X)d\theta \qquad (10)$$

In the context of updating continuous surveys using Bayesian estimation, $L(X|\theta)$ represents the likelihood over the observed data. That is, the OD matrix at t_{+1}. Similarly, $k(\theta)$ represents the prior distribution over the OD matrix at time *t*. The objective is to obtain the posterior distribution by updating the parameters of the prior using the input provided by the evidence. The next section explains the methodology in more detail.

2.5.2 Bayesian Methodology to Update OD Matrices Using Continuous Waves of Data

Let X = (X_1, … , X_p) be a vector of random variables that are jointly distributed with cdf:

$$F(x) \equiv F\left(x_1, \ldots, x_p\right) \equiv P\left\{X_1 \leq x_1, \ldots, X_p \leq x_p\right\} \qquad (11)$$

Alternatively, the vector X may be thought of as a row (or column) vector in an OD matrix. Since transportation planners tend to believe that the destinations of an OD matrix are more reliable than the origins (Meyer & Miller, 2001), vector X will be assumed to be a row vector, with each element of the row representing a destination. After that, it is imperative to define the distribution of the CDF. Since the random variables are concerned with counts, the joint distribution is potentially some multivariate form of the Poisson distribution (Maher, 1983). The multivariate normal distribution (MVN) provides a good approximation for means of counts that are not too small, as is the case in a typical OD matrix. Thus, the MVN is assumed to represent the likelihood over the observed data, denoted as $L(X|\theta, \Sigma)$. That is, it is assumed that X follows a MVN distribution with a j-dimensional mean vector θ and a positive definite and symmetric *i x j* variance-covariance matrix Σ.

$$X \sim N(\theta, \Sigma) \qquad (12)$$

$$\theta = \left(\theta_1, \ldots, \theta_j\right) \qquad (13)$$

$$\Sigma = \begin{pmatrix} \sigma_{11}^2 & \cdots & \sigma_{1j}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{i1}^2 & \cdots & \sigma_{ij}^2 \end{pmatrix} \qquad (14)$$

The diagonal (i.e. *i* = *j*) of the variance-covariance matrix represents the variance component of every element in vector X. In other words, every cell A_{ij}, where A is the total number of trip counts from origin *i* to destination *j* in the OD matrix is normally distributed with mean θ_j and variance σ_{ij}^2. The off-diagonal elements in the variance-covariance matrix capture the correlation between trips from various origins to a specific destination.

The MVN distribution can be given in terms of its density as:

$$f_x\left(x_1, \ldots, x_j\right) = \frac{1}{\sqrt{2\pi^j|\Sigma|}} exp(-\frac{1}{2}(x-\theta)^T\Sigma^{-1}(x-\theta)) \qquad (15)$$

The use of Bayesian updating involving the MVN distribution requires a prior distribution to be selected for each the mean vector and variance-covariance matrix parameters (Press, 1982).

Luckily, the MVN distribution has two conjugate prior distributions; a Gaussian prior over the mean and an inverse Wishart prior for the inverse of the covariance matrix Σ^{-1} (hereon referred to as the precision matrix). A conjugate prior provides a closed form solution for the posterior. That is, the posterior distribution can be analytically derived from the prior distribution and any new evidence (e.g. a new OD matrix) (Press, 1982).

Given a prior (denoted by the subscript 0) and new evidence, the posterior θ_m and the precision matrix ${\Sigma^{-1}}_m$ may be obtained using the following equations:

$$n_m = n_0 + m \qquad (16)$$

$$k_m = k_0 + m \qquad (17)$$

$$\theta_m = \frac{k_0\theta_0 + m\bar{x}}{k_0 + m} \qquad (18)$$

$${\Sigma^{-1}}_m = \left(\Sigma_0 + S + \frac{k_0 m}{k_0 + m}(\bar{x} - \theta_0)(\bar{x} - \theta_0)^T\right)^{-1} \qquad (19)$$

$$S = \sum_{i=1}^{m}(x_i - \bar{x})(x_i - \bar{x})^T \qquad (20)$$

Where:

$\bar{x}$ is the mean of the evidence vector
m indicates the iteration number
k_0 is the number of observations used to estimate the mean trip counts θ for the prior
n_0 is the number of observations used to estimate the mean trip counts θ for the prior and with sum of pairwise deviations for Σ^{-1}
S is the scatter matrix

The method prescribed above presents a simple solution for updating OD matrices using continuous data. Updating the matrices can occur at a time interval selected by the modeler or transportation authority. It is important to note, however, that this method is yet to be implemented, and thus open for improvement. It may be the case, for instance, that a more robust distribution should be assumed for the row vector of an OD matrix. The alternate distribution may not have a conjugate prior, hence requiring importance sampling to induce a posterior. Further, while correlations between a set of origins and one destination are captured in the proposed methodology, the destinations are assumed to be independent. A workaround may include repeating the above process for every row in an iterative manner. In sum, the intent behind the proposed methodology is to provide a stepping stone to fill the gap in the literature concerning updating OD matrices using continuous data. The application and the refining of the methodology are considered future research.

2.6 Chapter Summary

In this chapter, the literature concerning the determination of sample size for large household travel surveys was investigated. It was evident that even after more than 50 years of household travel survey design and implementation, the issue of sample size remains a contentious one governed by theoretical considerations, political will, and budgetary limitations. An empirical investigation was carried out to investigate the representativeness (as compared to the national Census) of one of the largest household travel surveys in North America, the TTS. It was realized that even with a sample of 159,157 households equivalent to 5% of the population, a 15% to 20% error margin existed for some key variables. Nonetheless, such an error margin may be acceptable for some transportation planning agencies. After that, an empirical exercise was conducted to expand on a methodology proposed by Smith (1979) identifying sampling rate requirements for the construction of statistically adequate OD matrices. It was concluded that sampling rates (and consequently sample sizes) are a function of the heteroscedasticity of travel behavior in the target population. It was also suggested that 1% sampling rate may be sufficient, at least for the purposes of the TTS to construct a reliable OD matrix that can accurately capture travel patterns on the regional level. The study of OD matrices and trip distribution was then expanded to the context of continuous surveys. As such surveys allow for the updating of OD matrices using continuous waves of data, a Bayesian methodology was proposed for updating purposes. Such a technique can enable transportation authorities to achieve a more accurate depiction of OD matrices while reducing the sample size requirements due to the ongoing collection of data. Nevertheless, little effort has been invested in understanding the practice of continuous surveys around the world. The next chapter introduces the state of practice of such surveys and discusses the implications of their use on demand modelling.

3 The State of Practice in Continuous Surveys

3.1 Basics of Continuous Surveys

In a full on-going continuous survey, data are collected for an entire weekday, every day of the week, 52 weeks a year (Ortuzar, et al., 2010). Such effort should ideally be kept going for several years. This data, collected over a large period of time, can potentially be used to observe temporal trends in travel patterns and behaviour in the survey area. The idea of using a continuous survey for collecting travel demand data is not new. As far back as the 1960s, Kish advocated for splitting a large cross-sectional survey into smaller repeated surveys with a relatively small interval time period (Kish, 1965).

Several European countries have adopted continuous surveys to monitor country-level travel behaviour over time. Examples include the French rolling census initiated in 2004, and the Netherland National Mobility Survey (NMS) in the Netherlands (Ortuzar, et al., 2010). The NMS was started in the Netherlands in 1978 and it is one of the oldest and longest standing continuous surveys. A third example is the National Travel Survey (NTS) in England, Scotland, and Wales, which has been going on since 1988. The NMS is a landline-based survey, while respondents are surveyed face-to-face in the NTS. Furthermore, several other continuous surveys are conducted on a regional level in other locations, such as the Sydney Household Travel Survey (HTS), the experimental continuous travel survey in Calgary (My Travel Log), and the experimental continuous survey conducted in Montreal. These region-wide surveys will be discussed in more detail later on in this thesis.

Table 3-1 and Table 3-2 provide a summary of a number of continuous surveys conducted over the last forty to fifty years. The original versions[28] of these tables are found in (Ortuzar, et al., 2010). As can be seen in Table 3-1, most continuous surveys collect 1-day trip diaries from the respondents. Ongoing region-wide continuous surveys of this nature can be found mostly in Germany, Austria, and Australia. As opposed to one-day surveys, a number of multi-day (panel) surveys are also evident, such as the Great Britain National Travel Survey, where survey

[28] Calgary's continuous survey, My Travel Log, was not included in the original Ortuzar table.

respondents completed week-long trip diaries. A week-long trip diary can greatly reduce the sample size required to accurately depict travel behaviour within a pre-specified area. Specifically, Stopher et al. estimated that a week-long GPS survey could lead to a 35% reduction of sample size as compared to a one-day survey (Stopher, et al., 2008).

Table 3-2 presents the sample size and response rates of a number of continuous surveys. Santiago de Chile, Sydney, and Montreal have adopted a sampling rate of 1% per year. The response rate of the region-wide continuous surveys has an average of approximately 61%, with a minimum of 25% (2002, Melbourne) and a maximum of 87% in Nuremberg. Nonetheless, an interesting observation is the high response rates experienced in Austria and Germany. This is primarily due to the implementation of the New Kontiv diary design which allows respondents to report their out-of-home activities for a pre-specified day using their own words (Ampt & Ortuzar, 2004).

All region-wide surveys to date (documented in the table), with the exception of Montreal and Calgary, have relied on some form of face-to-face interaction to collect data from respondents. In Australia, face-to-face interviews are the mode of choice, where survey respondents are visited twice by an interviewer. During the initial visit, the interviewer fills the household information of the respondents and hands them the trip diary to be completed for a specified day. The interviewer then collects the diary at the second visit. The latter visit can also be used to validate some of the respondents' answers (Ampt & Ortuzar, 2004). On the other hand, interviewers only visit respondents once in Austria and Germany. The respondents are handed the trip diary and asked to mail it back upon completion (Ortuzar, et al., 2010).

It is worth noting that only two Canadian cities, Montreal and Calgary, have attempted to run a continuous household survey. The Montreal and Calgary experiences are discussed in this thesis. Information has not been found to ascertain why other Canadian cities have not switched to the continuous model. Toronto, however, is in the process of assessing its current TTS. One of the objectives of this assessment is to investigate the feasibility of switching from a cross-sectional survey to a continuous model.

Table 3-1 Survey Description: Location, Timing, and Type

Country/Region	Period	Season	Panel	1 day	2 or 3 days	7 days	Long Distance[29]
Nation Wide Surveys							
The Netherlands	1978-onwards	All year	No	X	Before 1985		No
The Netherlands (LVO)	1984-1989	March-Autumn	Yes			X	Yes
Great Britain (NTS)	1988-onwards	All year	No			X	Yes
Denmark	1992-2003 2006-onwards	All year	No	X			1992-2000, 2010
Sweden	1994-2001 2010-2011	All year	No	X			Yes
German Mobility Panel (MOP)	1994-onwards	Autumn	Yes			X	2000-2003
Italy	2000-onwards	All year	No		X		No
New Zealand	2002-onwards	All year	No		X		No
Surveys in Metropolitan Areas							

[29] Long distance survey: Survey respondents that commute more than 70 km a day one-way

Country/Region	Period	Season	Panel	1 day	2 or 3 days	7 days	Long Distance[29]
Seattle: Puget Sound Transportation Panel (PSTP)	1989-2002	Various	Yes		X		No
Calgary: My Travel Log	2015-2016	All year	No	X			No
Montreal	2009-2011	All year	No	X			No
Santiago de Chile Mobility Survey	2001-2002 2004-2007	All year	No	X			No
Melbourne/Victoria (VATS and VISTA)	1994-2002 2007, 2009	All year	No	X			No
Sydney (HTS)	1997-onwards	All year	No	X			No
Perth and Regions Travel Survey (PARTS)	2002-2006	All year	No	X			No
South-East Queensland Travel Surveys	2003-2004 2007-onwards	All year	No	X			No
Nuremberg	1995-onwards	All year	No	X			No

Country/Region	Period	Season	Panel	1 day	2 or 3 days	7 days	Long Distance[29]
Burgenland and Lower Austria	1998-onwards	All year	No	X			No
Vienna	1998-onwards	All year	No	X			No
Leipzig	1999-2001	All year	No	X			No
Weisbaden	2002-2003	All year	No	X			No
Halle	2000-onwards	All year	No	X			No

Table 3-2 Survey Mode, Sample Size, and Response Rates Over Time

Country/Region	Period	Season	Mode	Sample Size (persons/year)	Response Rate
Nation Wide Surveys					
The Netherlands	1978-onwards	All year	RDD	46,000 (1985-1993) 333,000 (1995-1998) 42,000 (2010)	51% (1985) to 35% (1998) 70% (1999-2009)
The Netherlands (LVO)	1984-1989	March-Autumn	N/A	3,500 to 4,000	Low

Country/Region	Period	Season	Mode	Sample Size (persons/year)	Response Rate
Great Britain (NTS)	1988-onwards	All year	Face-to-face interviews	10,000 (1989-2001) 30,000 (2002-2008)	80% (1989-1991) 59% (2008)
Denmark	1992-2003 2006-onwards	All year	RDD	25,000 (pre 2002) 20,000 (2002-2003) & (2006-2009) 40,000 (post June 2009)	N/A
Sweden	1994-2001 2010-2011	All year	RDD	11,000 (1995-1998) 8,000 (1999-2001)	70% (1999-2001)
German Mobility Panel (MOP)	1994-onwards	Autumn	N/A	1,600 to 2,000	5 to 10%
Italy	2000-onwards	All year	RDD	15,0000	N/A

Country/Region	Period	Season	Mode	Sample Size (persons/year)	Response Rate
New Zealand	2002-onwards	All year	Face-to-face interviews & GPS (2015)	4,400 (2002-07) 9,200 (2008-onwards)	70%
Surveys in Metropolitan Areas					
Seattle: Puget Sound Transportation Panel (PSTP)	1989-2002	Various	Phone-interviews	3,000 to 4,000	N/A
Calgary	2015-2016	All Year	Mail	6,000	N/A
Montreal	2009-2011	All year	RDD (landline plus cell)	30,0000	
Santiago de Chile Mobility Survey	2001-2002 2004-2007	All year	Face-to-face interviews	30,000 (2002) 10,000 onwards	70% (2002) 45% (2007)
Melbourne/Victoria (VATS and VISTA)	1994-2002 2007, 2009	All year	Face-to-face interviews	10,000 to 12,000	60% (1994) 45% (1999) 25% (2002)

Country/Region	Period	Season	Mode	Sample Size (persons/year)	Response Rate
Sydney (HTS)	1997-onwards	All year	Face-to-face interviews	10,000	75% (1997) 68% (1999) 63% (2004)
Perth and Regions Travel Survey (PARTS)	2002-2006	All year	Face-to-face interviews	5,000	48% (2003) 49% (2004) 57% (2005) 60% (2006)
South-East Queensland Travel Surveys	2003-2004 2007-onwards	All year	Face-to-face interviews		N/A
Nuremberg	1995-onwards	All year	Drop-off and mail back	14,500 to 19,000	87%
Burgenland and Lower Austria	1998-onwards	All year	Drop-off and mail back	39,000	N/A

Country/Region	Period	Season	Mode	Sample Size (persons/year)	Response Rate
Vienna	1998-onwards	All year	Drop-off and mail back	19,000	N/A
Leipzig	1999-2001	All year	Drop-off and mail back	5,300	80%
Weisbaden	2002-2003	All year	Drop-off and mail back	5,000	N/A
Halle	2000-onwards	All year	Drop-off and mail back	10,500 to 15,000	82%

3.1.1 The Disadvantages of Cross-Sectional Surveys

A cross-sectional survey has several drawbacks when used for household travel surveys. A key issue is that respondents are asked to provide responses for only one weekday, and this collection occurs over a short time period, e.g. September to December. As a result, such data are pooled and assumed to be representative of a "typical day" of the year. However, the specific time period where the survey is undertaken may be subject to unpredictable events (Stopher & Greaves, 2007). For example, a survey conducted during the 2008 recession would not provide an accurate depiction of regular travel patterns and behaviour. In addition, a cross-sectional survey does not allow for the comparison between short term and long term trends, as data are only collected at a point in time (Kish, 1965).

From the logistical side, the unavoidable loss of experienced staff and knowledge during the gaps between cross-sectional surveys is also an alarming issue. It requires new surveyors or third party firms to be contracted each round, who would need to take the time to be familiarized with the task and be trained accordingly. Consequently, the rebuilding of a team to conduct a large one-off survey introduces a high ramp-up cost every five or ten years (Ortuzar, et al., 2010).

3.1.2 Advantages of Continuous Surveys

A key aim of a continuous survey is to capture the changing social and economic conditions over time (Ortuzar, et al., 2010). For example, it is expected that a regional travel continuous survey should be capable of depicting the 2008 recession by observing a decline in the number of work-related trips. Furthermore, a similar survey should also be able to capture the effect of the current decrease in fuel prices on mode choice. In this way, the global evolution of mobility behaviour over time can be captured.

Due to the sustained data collection effort, a continuous survey exhibits a number of advantages over a one-off large cross-sectional survey. First, a large stream of continuous data can be used to depict travel patterns and behaviour over time, whether it be months, seasons or years. Such depictions can reflect changing social and economic conditions within the study area, such as a change in mode choice as a result of fluctuating fuel prices and seasonal effects. It also allows for special surveys, such as panel surveys to be conducted to capture unique travel behaviour (Stopher & Greaves, 2007). In addition, provided that a continuous survey is conducted over the entire week, the average weekend trip rates and travel patterns may also be captured.

Next, it is believed that greater value can be derived from a team that is employed on an on-going basis, as compared to a team that is established for a short period for a cross-sectional survey and then subsequently dismantled. From the budgetary perspective of funding agencies, it may be easier to obtain funds when an on-going survey is established, than for a large one-off cross-sectional survey every five or ten years. That is, the perpetual nature of the survey allows for easier budgeting for municipalities (Stopher & Greaves, 2007).

Finally, from a modelling and statistical investigation perspective, the continuous nature of the data may permit the use of more sophisticated models to investigate dynamics and adaptation of travel behaviour (Ampt & Ortuzar, 2004). Assuming that a statistically adequate Origin-Destination (OD) matrices can be generated, the updating of OD matrices for the study area can reflect the differential growth of mobility, filtered by mode and trip purposes. In addition, the short and long term impact of transport policies, and the correlation of changes in transportation demand with changes in supply (i.e. addition of infrastructure, construction season impacts) may also be assessed with continuous travel data.

3.1.3 Disadvantages of Continuous Surveys

Theoretically, a continuous survey has several advantages over a cross-sectional survey, but there are some potential pitfalls. Foremost, there is the possibility of insufficient data to meet the needs of a conventional travel demand model (trip-based four-stage model) or other more advanced models (e.g. activity-based models). For instance, the American Community Survey - a general purpose continuous survey conducted in the US to collect data on employment, education, transportation and much more (United States Census Bureau, 2015) - was under heavy scrutiny in 2005 (Stopher & Greaves, 2007). Transportation planners cited serious problems in the survey, such as large standard errors as a result of the small annual sample size limiting the ability of planners to make reasonable conclusions. Another example of unsatisfactory results was the National Travel Survey in Sweden, where a continuous data collection effort was discontinued despite a decent sample of 8,000 individuals per year (Ortuzar, et al., 2010). This was due to the fact that transportation planners were unable to detect large changes in travel behaviour, and to follow overall travel developments over time except when examining yearly changes. In fact, most of the changes in travel behaviour were minimal from one year to the next. Furthermore, data quality declined over time due to the loss of experienced interviewers and staff. Santiago De Chile faced a similar data quality problem, where some completed surveys were only inputted after 4 months of interviewing respondents (Ortuzar, et al., 2010). It is worth noting, however, that most reported problems in the literature referred to continuous surveys at the national scale.

Next, a poorly designed continuous survey may result in household selection bias, where surveyed households become clustered in specific areas (Ortuzar, et al., 2010). Ideally, the survey should be evenly spatially distributed, which could prove to be a difficult task when taking into consideration non-response and the temporal nature of the data collection process. Proper weighting and expansion methods should be derived to account for the temporal variation within the data (Ampt & Ortuzar, 2004). In addition, the temporal variability within the data may introduce noise, and as a result, data may also be rendered useless for the first few years of a continuous survey, until sufficient time has passed to collect a statistically significant sample size for various types of models (Ampt & Ortuzar, 2004).

Finally, while reduced cost is often put forth as a positive for continuous surveys, they are not necessarily cheaper than cross-sectional surveys (Peachman & Battellino, 2007). The cost is simply distributed over a longer time period. Efficiency gains can be achieved, however, as processes are streamlined and a definite annual budget is set.

3.1.4 Panel vs. Repeated Cross-Sectional or Continuous Surveys

Panel surveys differ from continuous or repeated cross-sectional surveys. A panel survey is concerned with gathering information for a predetermined set of individuals or households over a series of time points, or "waves" (Miller, et al., 2012). The same survey is repeated at every time period with a predetermined population subset. This approach has many advantages such as identifying the impact of time-related effects, including habit and inertia in transport (Yee & Niemeier, 1996), and allows for a substantial reduction of sample size. On the other hand, repeated cross-sectional/continuous data are sampled from the wider population with no replacement. In other words, the same household or individual are not sampled twice (unlike a panel survey). Continuous data does not allow observing habit formation on the micro scale; however, they do allow for the observation of macro trends within the transport and spatial economy (Yee & Niemeier, 1996).

Unfortunately, panel surveys usually fail to include all segments of the population (different age groups, specific mode shares, etc.), and may lack in proper spatial coverage. Even if an effort is made to develop such a balanced panel, the sample would age/change over time, and thus would require continuous updating (Ampt & Ortuzar, 2004). Furthermore, respondents may not be willing to keep up with the program as fatigue and other factors, including unexpected life events, occur. This may result in missing data or data attrition (Stopher & Greaves, 2007). As a result, the selected sample dataset representation of the wider population can be questioned, due to an increase in bias. One method to reduce bias would be to use sampling weights to adjust trip rates, but the calibration of such weights requires a large cross-sectional dataset (Ortuzar, et al., 2010).

As an illustrative example, a study that compared the statistical robustness of panel and cross-sectional data, using the Puget Sound Transportation Panel dataset, can be referenced (Yee & Niemeier, 1996). The study showed, through an example, that the standard errors of continuous data were large whenever large variations between individuals existed. Therefore, the power to detect statistically significant differences in the estimates could be undermined. On the other hand, using panel data, it was possible to focus on within-subject change and make population inferences accordingly. It can be argued, however, that the objective of a regional household travel survey is to capture macro-level variation, potentially at the zonal level, therefore undermining the importance of individual-level differences.

The choice between a panel and continuous dataset is intertwined with the objectives of the stakeholders involved. A continuous dataset is capable of capturing the aggregate effects split by demographic and/or mode. A panel dataset is, instead, more suited to monitor changes in travel activity due to individual attributes. Finally, a continuous survey is more suited to represent the core of the data collection effort, while a panel survey may augment the core of a typical cross-sectional survey.

3.2 Sample Size, Weighting and Validation of Data

The required sample size to allow for statistically meaningful data from continuous household travel surveys has not received rigorous attention by researchers. There have, however, been a few studies on the determination of sample size, weighting, expansion and data validation techniques for continuous surveys. A summary of these examples is provided in this section.

3.2.1 Sample Size, Pooling and Aggregation Techniques

The decision on the appropriate sample size for any multi-objective survey is controversial in nature (Stopher & Jones, 2001). For example, the Montreal Regional OD Continuous Survey divided the sample size of a typical cross-sectional survey over the 4 years of the continuous data collection time frame. This produced a sample size of approximately 1% for each year. On the other hand, the Sydney HTS adopts a much smaller sample size of 3,000 households per year, the sum of which over a four-year period represents approximately 1% of the Greater Sydney Area population.

At the heart of the decision of what sample size to use is the generation of statistically adequate OD matrices. This is because the data size requirements for trip generation and mode choice modelling are usually small in comparison to trip distribution (OD) matrices (Smith, 1979). Michael E. Smith (1979) argued that if an interchange is to have a volume of 1000 trips at 90% confidence and a 25% level of accuracy, a 4% sampling rate is required (Smith, 1979). Nonetheless, the above argument falls short for continuous surveys, where OD matrices should be periodically updated. Cools et al. (2010) calculated the Mean Absolute Percentage Error (MAPE) of OD matrices for different sampling rates generated using the Belgium national census (Cools, et al., 2010). They concluded that an OD matrix reproduced from a sampling rate of 1% has a MAPE of 19%. A methodology for updating OD matrices using Bayesian methods was proposed in chapter 2.

Using proper pooling techniques for continuous survey data is also very important to produce a representative sample. Data pooling involves combining more than one source or year of data to form a “pooled” dataset and estimating econometric models using that dataset (Siikamaki & Layton, 2007). The literature provides one method of pooling techniques within the Australian context. The Sydney household travel survey followed their 1996 cross-sectional survey of 12,000 households with a continuous survey which has since been in place. A relative standard error estimate of each year, as compared to the base year, was calculated to determine the pooling frequency required to simulate the data comparable to a one-off large cross-sectional survey. A 3-year pool seemed appropriate, with a longer period providing a minimal reduction in errors (Peachman & Battellino, 2007). This approach provided a happy medium, where a sufficient sample size was available for modelling while accounting for temporal variability. The sample was spread geographically and temporally, capturing all traffic analysis zones across the 4 seasons and the 12 months of the year (Peachman & Battellino, 2007).

Ampt & Ortuzar (2004) provide another alternative to simply pooling data. They suggested starting with a bigger survey – e.g. three times the predetermined continuous sample size – for the first year. This overcomes the "cold start" problem of continuous survey efforts, where no data are available for statistical analysis in the first few years of a study. The Year 2 sample can then be integrated with year 1 using the multi-proportional weighting technique (See Section 1.2.2).

Data fusion is also an attractive option to increase the sample size and the "richness" of continuous travel survey data. However, the underlying assumption of the transferability of data across space and time needs to be carefully investigated. Further, the usefulness and viability of data fusion techniques have to be assessed on a case-by-case basis. (Stopher & Greaves, 2007)

3.2.2 Weighting

The design weight is the average number of units, be it persons, households or trips, in the surveyed population that each sampled unit represents (Kish, 1965). Traditionally, the weight for the unit is assigned using the inverse of the inclusion probability. The inclusion probability is calculated by dividing the sample size by the true population size, which can be obtained from the census for example. That said, for the case of a continuous survey, it is important to develop a weighting process that takes into account variations over time (Ortuzar & Willumsen, 2011). Ampt and Ortuzar advocate for the use of the multi-proportional method for updating "important variables" such as household size, number of vehicles owned, etc. (Ampt & Ortuzar, 2004). A simple explanation is provided below:

1. Select the parameter of interest for weighting – example: household size
2. Outline the sample proportions for each household size category (1 to 6 for example) for year 1 and year 2. The proportions should be displayed in absolute numbers and percentages.
3. Calculate the weight adjustment factor by dividing the year 2 proportion percentage by that of year 1.
4. Multiply year 1 absolute proportions by the adjustment factor to get the true sample of the category
5. Sum up the samples from year 1 and 2 to represent the up to date sample distribution

This method accounts for variations in year *t* and *t*-1 in how the sample proportions are distributed (mean and variance of each category). Areas of low variance do not need to be weighed in such a manner. If the sample year corresponds with a census year, then traditional weighting against the census can be used. Furthermore, imputation methods can be used to fill in missing values. Examples include using the zonal mean to fill in an empty cell (Ampt & Ortuzar, 2004).

Another measure for weighting and pooling continuous data was presented in a feasibility study for Calgary's continuous household travel survey program (Zmud, et al., 2011). Similar to many regions around the world, the City of Calgary has conducted its cross-sectional survey in the past to coincide with the Federal Census years to allow for proper expansion of population variables. It is expected that the Federal Census data will continue to be used for expansion purposes if Calgary decides to make the move to a continuous survey. However, the weighting approach will be affected by the chosen period increments in which the collected survey data will be processed and aggregated for use. RAND Corporation, one of the main consultants for the City of Calgary on the continuous survey program, outlined a methodology for weighting data at a 1-year time increment (Zmud, et al., 2011):

1. Obtain base weights by calculating the inverse probability computed for all selected households.
2. Estimate the variation in monthly response factor to compensate for the variations in the number of sample cases resolved across months.
3. Estimate the variation in weekday response factor to compensate for the variations in the number of sample cases resolved across days of the week.
4. Adjust for housing unit nonresponse.
5. Adjust weights obtained from steps 1 to 4 by conforming them to the independent housing unit estimate extrapolated from the last census.
6. Repeat step 5 for population counts of major demographic subgroups.
7. Obtain the final household weight following an iterative process where each household is categorized based on household and person characteristics. That is, the previously calculated weights are iteratively adjusted based on these categories.
8. Round all weights to the nearest integer

This same 8 step process can be employed for any time increment, such as 3, 5 or 10 years by taking the existing weights on each of the 1-year increments and dividing them by the number of years involved (Zmud, et al., 2011). It is worth mentioning that RAND corporation recommended the consolidation of data over a 3-year period, given the small sample size employed.

3.2.3 Validation

It is very difficult to statistically assess the adequacy of survey results. Making comparisons with a census or other surveys is troublesome as the instruments and techniques used can vary, leading to an increase in bias (Stopher & Jones, 2001). Nonetheless, some validation schemes have been found in the literature.

Using GPS assisted sub-sample data for validation is one such scheme (Stopher, et al., 2007). Through the use of GPS, the entity in charge of surveys can check if the respondents accurately report trip start and end times, trip lengths and distances, and trip origins and destinations accordingly. Nonetheless, a representative sample is needed to provide significant results. In addition, the survey instruments and techniques in use must match those used by the non-GPS survey respondents.

Another method of validation, specifically to check whether the interviewer completed his/her workload, is by randomly dialing/visiting/connecting with the respondents and asking them predetermined questions (Peachman & Battellino, 2007). Such questions include whether they have completed the survey and ask about basic socio-demographic info. This method can be extended to verify trip rates on another 24-hour day assigned to the respondent. In Sydney, for example, 10% of all interviewer completed workloads are validated using this method.

3.3 Regional Continuous Household Travel Survey Examples

3.3.1 Summary of the Sydney Household Travel Survey

Sydney has one of the oldest continuous household surveys. The Sydney HTS was initiated in 1997 with an annual sample size of 5,000 households, equivalent to 1% of Sydney's population, over a 4 to 5-year period (Peachman & Battellino, 2007). The data are used to generate transport trends in the Sydney Greater Metropolitan Area (GMA), undertake a detailed analysis of areas or transport corridors, and to provide input to the Sydney Strategic Travel Model (Bureau of Transport Statistics, 2013). Prior to the continuous survey, Sydney instead conducted a large cross-sectional survey every 10 years. The region decided to switch to a continuous survey with the objective of collecting more timely data to meet their transportation needs (Ampt & Ortuzar, 2004). Each survey period starts on a Sunday in the Month of June and ends on a Saturday in June of the following year (Bureau of Transport Statistics, 2013).

The GMA (also known as the GSMR or the Greater Sydney Metropolitan Area) consists of Statistical Divisions (SD), Statistical Subdivisions (SSD), and 80 Statistical Local areas (SLAs). The SDs and SSDs are the equivalent of the Statistics Canada Census Division and a Census Subdivision in the GTA. An SLA, however, is a bit larger than a typical GTA Dissemination Area.

3.3.1.1 Survey Mode and Method

A multi-stage stratified sampling technique has been adopted for data collection. This involves first randomly selecting Travel Zones (TZs) within SLAs. A random dwelling is then selected within a random block in that TZ for surveying. The sample is spread spatially and temporally to cover all geographic areas and days of the year. However, all surveys are conducted face to face, with an invitation by mail sent two weeks prior to the interview. All household residents are interviewed, with each member asked to recall travel activity over a 24-hour period. (Bureau of Transport Statistics, 2013)

3.3.1.2 Sample Size and Pooling Technique

The sample size for the continuous survey was estimated by calculating relative standard errors (RSEs). Using the cross-section survey of 1991 as a base year, Sydney estimated the RSEs comparing aggregated or averaged values of yearly waves with the 1996 base survey (Figure 3-1).

The metropolitan agency concluded that the variation at the SLA becomes minimal after 3 years, with the exception of some SLAs. Therefore, the agency decided to use a method of optimal allocation, potentially over-sampling SLAs with a large variation versus SLAs with a much smaller reported RSE. From this, the conclusion was to use a sample of between 3,000 to 5,000 households annually. The maximum acceptable threshold for an SLA's RSE was identified at 10%. (Bureau of Transport Statistics, 2013)

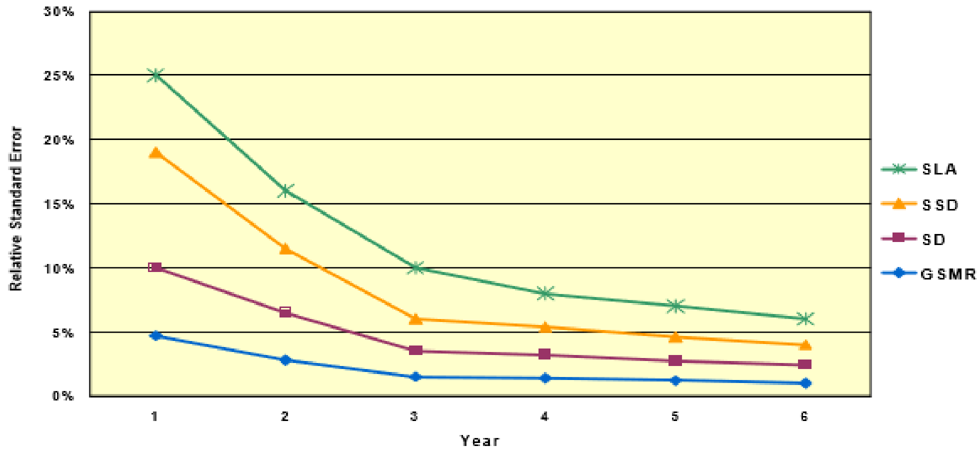

Figure 3-1 Relative Standard Errors for Trip Estimates at Varying Spatial Units[30]

3.3.1.3 Weighting and Expansion

For weighting and expansion, Sydney uses both pooled and annual approaches. The pooled approach involves pooling three years of survey data to produce one dataset, which is then weighted and expanded to represent the wider population. On the other hand, for the single year approach, estimates are weighted for a one-year period of the HTS. Weighting is conducted on three levels: household, individual, and region day factors. For household, the inverse of the probability of selection is used for weighting. Household population benchmarks are required for post-stratification weighting and expansion and are usually obtained from the most up to date census. Weighting adjustments are then executed at the SLA level to provide an adequate representation of household types across all 80 SLAs. The same approach is followed for person weighting. The main variables of interest are age and sex. As for the final level (region day), every day of the week is considered as a sub-sample. The aim is to have equal representation of sample sizes and proportions, and so exact day factors are computed accordingly and applied only at the region level. (Peachman & Battellino, 2007)

---

[30] Figure copied from (Peachman & Battellino, 2007)

3.3.2 Summary of the Montreal Experience

An experimental continuous OD survey was conducted by the Agence Métropolitaine de Transport (AMT) in Montreal. The survey started in January 2009 and ended in December 2012. The overarching goal was to add value to the regional Montreal cross-sectional 4-year surveys, conducted in 2008 and 2013 (Tremblay, 2014). Approximately 15,000 households were surveyed per year. The sample size was determined by splitting the typical 4% to 5% cross-sectional survey over a 5-year period. In other words, the total sample surveyed was about 63,000 households, which is equivalent to the total number of households surveyed in a 5-year transportation plan. The survey was conducted in a similar fashion to that of Sydney; i.e. in three waves every year.

The continuous survey had three main objectives, paraphrasing from a presentation by Pierre Tremblay's, head of the transportation systems modelling unit at the Ministry of Transportation in Quebec (Tremblay, 2014):

- Develop annual and seasonal mobility pictures
- Produce high-level indicators to monitor progress towards policies and transportation plans targets (e.g. annual reports)
- Maintain technical & organizational knowledge / staff experience between [the two] 5-year large-scale surveys

AMT has yet to produce a report summarizing the design, implementation and main findings of their continuous survey. The Montreal continuous survey details mentioned below can all be found in Pierre Tremblay's presentation (Tremblay, 2014).

3.3.2.1 Sampling Frame, Survey Modes and Instruments

The sampling base of the continuous Montreal survey was a hybrid of cell phone, land-line, and web-based survey tools. The 2008 questionnaire was unadjusted for the continuous survey except for the addition of some new questions on disability mobility, auto availability and respondent arrival time. The addition of the 3 questions cost nearly one additional minute on average in interview time. The final results were expanded based on the 2011 census.

The planning agency, in an attempt to capture households with no landlines integrated a cell phone based sample. Both a validated cell phone list and random digit dialing was used. The validated list came with a cost of $4/person, while random digit dialing only cost 4 cents/person. However, the productivity and completion rate of the validated list was approximately 23 times that of the randomly dialed list, and most randomly dialed individuals had a landline. The cell-based sample proved to be quite young with most individuals lying in the lower income, no car, and no kids demographic with a preference for active and/or transit mobility.

A postal address sampling frame was also used. The addresses in the list were validated against the current list of landline-based households. Households that happened to be on both lists were taken out. The remaining survey population was asked to fill the survey using the Polytechnique's Web-Survey tool. A completion rate of only 7% was achieved (135 households). This may be explained by the fact that respondents were only sent a link via mail to complete the survey. Furthermore, the recipients of the mail invite did not receive a follow-up call. No apparent differences in socio-demographics and travel behaviour were noted between the landline based and postal based sampling frames.

3.3.2.2 Data Collection, Staff Management, and Continuous Reporting

It is a complex task to select personnel, train them and keep them all motivated throughout the survey process. During the execution years of the Montreal continuous survey, it took the call centre 2 months to reach a completion rate of 3 interviews/hour, including some time spent to fine tune the utilized software tools. The firm in charge conducted continuous training activities to keep the interviewers up to the task. Furthermore, staff turnover was minimized by introducing incentives and rewards on a regular basis. Examples of incentives and motivation strategies included: keeping interviewers aware of their performance metrics and quality indicators, initiating a $50 monthly draw prize for the best performing interviewers, and giving the best interviewers the opportunity to be part of the survey design team.[31]

After collecting the data, basic respondents' details were immediately verified, and their respective addresses were geocoded automatically. Invalid interviews were also immediately

---

[31] The information regarding on the job interviewer incentives were relayed by a colleague who interviewed one of the team members of the Montreal continuous survey team

rejected while missing values were imputed on the go. Aggregated results were reported on a yearly basis.

3.3.2.3 Status of Current Results

To date, AMT has found it difficult to fit the existing results with the 5-year trends (Tremblay, 2014). In addition, the fall sample has been reported to be too thin to measure significant annual variations at the sub-district level. Thus, seasonal trends were subsequently difficult to capture. The 2013 cross-sectional survey will assist in the validation of the continuous survey results as the surveying team will be able to verify whether the trends captured through the continuous survey fit the 2013 large cross-sectional survey. Other problems, as previously touched on, include the specification of the sampling frame and the staff management.

3.3.3 Summary of the City of Calgary Experience

In the past few decades, the City of Calgary has witnessed an increase in economic growth and, consequently, travel demand. Further, variations in mode behavior across different population cohorts have been recorded. Therefore, The City of Calgary has investigated the feasibility of switching from a cross-sectional household travel survey, last conducted in 2011, to a continuous household travel survey. The proposed continuous household travel survey is intended to address two main objectives (Resource Systems Group, 2014):

1. Provide household activity data to update the Calgary Regional Transportation Model (RTM)
2. Monitor and report spatial and temporal travel patterns across modes as part of the "Plan It Calgary" transportation program[32]

The results of the feasibility study have prompted the city to move forward with a 2-year pilot program titled "My Travel Log", where a sample of 1,500 households each year will be surveyed in Calgary and its neighboring regions of Rocky View County, Wheatland County, and the Municipal District. The pilot program was initiated in 2015 and is currently still being implemented (The City of Calgary, 2016).

[32] Plan It Calgary – the new Calgary Transportation Plan – requires transportation related patterns and statistics to be reported once every three years over a 9-year period.

This section summarizes the discussion and recommendations obtained from the continuous survey feasibility analysis for the City of Calgary, along with the methods implemented in the pilot study.

3.3.3.1 Survey Mode, Method and Sampling Frame

In order to successfully conduct the continuous household survey, a mixed methods survey approach was proposed by Resource Systems Group (RSG) Inc - the City of Calgary's primary research consultants on this project (Resource Systems Group, 2014). The mixed approach consists of a web tool provided by RSG, along with the use of telephones to conduct interviews. An address-based sampling frame was employed through making use of the City of Calgary's Tax Assessment Address Database, in addition to other private vendors for rural areas. The residents of the aforementioned areas are to be initially recruited by Canadian mail, followed up by a telephone call(s). Incentives such as gift cards, raffle prizes or cash will be used to incentivize participation in the survey. An activity diary will be included in the mail package sent to participants. The mail package will also contain information about the survey, and the suggested date for recording all trip related activities. The participant can then copy the details recorded onto the web-tool, or narrate them via telephone to the city.

3.3.3.2 Sample Size

The 2011 Calgary Household Travel Survey (HTS) consisted of 11,000 households. Therefore, a sample size of 11,000 households over a 10-year period was proposed for the continuous survey (Zmud, et al., 2011). This is equivalent to 1,100 households per year. Approximately 80% of these households are to be in the City of Calgary with the remaining 20% located in the surrounding regions. The data are to be collected over a 7 months' period per year (January to the end of April, and September to the end of November). Thus, a sample size of approximately 157 households will be surveyed per month, assuming an evenly distributed surveying effort. In the case of the pilot study, 1,500 households are being sampled per year (Resource Systems Group, 2014). The survey administrator has also outlined an objective of 100 households per week. The survey is conducted on both weekdays and weekends, including holidays.

3.4 Model Development Using Continuous Survey Data

Continuous travel surveys present the best survey design to provide up-to-date data. Nonetheless, for a continuous survey to act as a suitable substitute for the traditional cross-sectional dataset, regional stakeholders must be capable of using the data to build and calibrate at least four stage transportation models.

Many continuous and/or panel surveys provide input data for travel demand models. Nevertheless, in the case of surveys conducted on the national level, this input is rather secondary. The data provided from continuous elements is mainly used for locales where regional data are missing, or to calibrate and cross-validate model outcomes. That said, data from regional continuous surveys have been used in all stages of travel demand models. Table 3-3 below provides a summary of how data from a number of continuous surveys have been put in use (Zmud, et al., 2011):

Table 3-3 Data Use of Continuous Travel Surveys Around the World

Survey	Type	Year	Sample Size	Motivation and Data Use
British National Travel Survey	Continuous Multiday	2002 – Ongoing^	8,000 households per year	- Provide statistics on travel behavior - Providing data for demand modelling is not an objective for the NTS
German Mobility Panel	Annual Multi-Day Panel (3 Year cohort)	1994-Ongoing	1,500 individuals per year	- Provide up-to-date data for transport policy at the national level - Mostly used as input to travel generation model steps - Also used to calibrate other model steps
Danish National Travel Survey	Continuous	2006 - Ongoing	11,000 individuals per year	- Provide statistics on travel behavior - Providing data for demand modelling is not an objective for the Danish NTS

Dutch National Travel Survey	Continuous	2004 - Ongoing	20,000 households per year	- Provide statistics on travel behavior - Mostly used as input for travel generation model steps - Important source for cross-validation of local travel demand models
Rhein-Maine Regional Panel Survey	Annual Multi-Day Panel	2008 – 2011	700 households per year	- Provide statistics on travel behavior - Data were used in all stages of a travel demand model; Model was never updated after completion and survey was discontinued
Victoria Activity and Travel Survey	Continuous	1994 - 2002	5,000 households per year	- Describe travel patterns in Melbourne - Provide information for transport planning and modelling
Sydney Household Travel Survey	Continuous	1997 – Ongoing	3,000 households per year	- Describe travel patterns in the Sydney Greater Metropolitan Area - Provide information for transport planning and modelling
Perth and Region Travel Survey	Continuous	2002 – 2006	2,600 households per year	- Describe travel patterns in Perth - Provide information for transport planning and modelling
Victoria Integrated Survey of Travel and Activity	Continuous**	2007 – Ongoing	11,000 households per year	- Describe travel patterns in Melbourne and Regional Cities in Victoria - Provide information for transport planning and model calibration
New Zealand Ongoing Household Travel Survey	Continuous	2003 - Ongoing	5,000 individuals per year	- Describe travel patterns in New Zealand

Montreal Household Travel Survey	Continuous	2009-2013	5,000 households per year	- Provide statistics on travel behavior
Calgary Continuous Survey – My Travel Log	Continuous	2015-2016	1,500 households per year	- Provide statistics on travel behavior - Input for travel demand model

*Fieldwork was carried out twice a year
** Year-on/ year-off,
^Name and Sampling Frame Changed

As can be seen from the table above, data from continuous surveys is not usually used as the main input for travel demand models. Nevertheless, exceptions do exist on the regional level, such as the case in Sydney and Calgary. The reason is that continuous and annual surveys provide data more frequently than the need of many travel demand models. Further, comparable homogeneous groups tend to exhibit stable behavior over short periods of time, eliminating the need for the continuous updating of travel data (Zmud, et al., 2011). Continuous data are mainly used in the provision of periodic transportation-related statistics and investigating travel behavior.

3.5 Investigating Travel Behavior and Trip Generation Using Continuous Data

Trip generation is defined as the total number of trips generated by a household (or a person). The trip may originate from or end at a household (Ortuzar & Willumsen, 2011). The two main forms of trip generation in use today are linear regression and cross-classification tables. Linear regression is a statistical process estimating the relationship between variables, for example, between trip generation from a household and a set of personal, household and/or zonal attributes. Cross-Classification tables are similar to regression in the sense that trip generation is captured, but the number of variables or categories factored is limited. The method, however, has two main drawbacks. The sample size required for generating cross-classification tables is typically large, and the method assumes that trip generation rates are stable over time (Ortuzar &

Willumsen, 2011). As the main objective of a continuous survey is to capture temporal trends in trip behavior, trip generation via linear regression is most appropriate.

Continuous survey data can be used to periodically update regression model parameters once new datasets are available through the use of Bayesian statistics. Bayesian statistics, commonly referred to as Bayes Theorem, represent a formal mechanism that combines new information (such as data collected from a continuous survey) with available information (Dey & Fricker, 1994). A more elaborate discussion of Bayes Theorem can be found in (Train, 2009). Nevertheless, an illustration of how to apply Bayesian statistics to update trip generation rates estimated by regression is provided below.

A prior distribution (i.e. distribution of weighted trip generation rates) is assumed to be normal with mean t_1 and variance S_1^2, $N(t_1, S_1^2)$ (Ortuzar & Willumsen, 2011). The prior distribution may represent the base dataset (data collected at year 1). The sampling distribution (distribution of trip generation data collected at year 2 for example) is also assumed to have a normal distribution of mean t_s and variance S_s^2, $N(t_s, S_s^2)$. The mean t_2 and variance S_2^2 of the posterior distribution (year 2 trip generation rates) can then be obtained using the following formulas:

$$t_2 = t_1 \frac{\frac{1}{S_1^2}}{\frac{1}{S_1^2}+\frac{1}{S_s^2}} + t_s \frac{\frac{1}{S_s^2}}{\frac{1}{S_1^2}+\frac{1}{S_s^2}} \qquad (21)$$

$$S_2^2 = \frac{1}{\frac{1}{S_1^2}+\frac{1}{S_s^2}} \qquad (22)$$

Practical examples may be found in Ortuzar's and Willumsen's book "Modelling Transport" (Ortuzar & Willumsen, 2011), and in (Dey & Fricker, 1994). However, a linear regression based generation model may not necessarily capture seasonal, spatial and many other underlying effects, unless separate models are estimated for separate regions, seasons, etc. That is, it does not provide a comprehensive framework for capturing all underlying effects within a single and robust modelling formulation. Moreover, one of the key assumptions of simple linear regression is the independence of observations. Therefore, it may be inadequate to build trip generation models on continuous datasets using simple linear regression due to the time series nature of the data.

In a continuous dataset, the events or trips happening in zone *j* at time $t = 1$ are likely to be correlated with trips occurring in zone *j* at time $t = 2$. This violates the assumption of independence for linear regression. Continuous survey data can be exploited to develop a more robust modelling approach, which is known as mixed effects/multilevel econometric framework (DiPrete & Grusky, 1990). A multilevel econometric framework can be perceived as a hierarchy of a system of equations, where the individual or household level variation within each spatial and temporal unit can be explained as a function of different variables (DiPrete & Grusky, 1990). For example, individuals are grouped within their respective households and households are grouped within specific zones. Similarly, days are part of weeks, weeks are part of seasons, etc. The main objective of assuming such a natural hierarchy of demand generating units is to differentiate dimensions of variations in demand/behaviour. Such a multilevel approach for modelling travel demand can capture systematic and random variations of travel behavior across individuals, individuals within households, households within zones, zones within regions, as well as variations across temporal variables such as weeks, seasons, years, etc. (Rabe-Hesketh & Skrondal, 2012). A more mathematical description of the mixed effects econometric framework may be found in chapter 5.

Several countries and metropolitan regions around the world have conducted continuous household travel surveys (see Table 3-1). Nevertheless, it is very difficult to find literature on the statistical modelling tools and techniques used with continuous data to depict transportation behavior. On the other hand, several types of researches have opted to use (repeated) cross-sectional and panel datasets to depict behavior. In numerous cases, the statistical model of choice was a mixed effects model[33].

DiPrete and David Grusky (1990) developed a multilevel model for the analysis of trends within repeated cross-sectional samples. The proposed model is first-order autoregressive at the macro-level equation (highest level in the multilevel model), defined to be a time variable such as year, as opposed to off-the-shelf software tools (including those in SAS, Stata, and R) that only allow

---

[33] A mixed effect model is also known in literature as a multilevel model, hierarchical linear model, and random intercept/coefficient model (Rabe-Hesketh & Skrondal, 2012)

specifying correlations at the micro-level. Such a custom model allows for time series analysis by serially correlating the errors of the upper-level equation (DiPrete & Grusky, 1990).

A less programming intensive approach was presented by Lipps and Kunart (2005), where they used four cross-sectional data sets of the NTS conducted in (West) Germany in 1976, 1982, 1989 and 2002 to build a hierarchical linear model (Lipps & Kunert, 2005). The dependent variable of the model was the logarithmic transformation of the daily travel distance covered by the survey respondents. The dependent variable was regressed against a series of socio-demographic and land use variables, such as employment, number of cars available, population size and household size. The structure of the model was setup so as to have individuals nested within households nested within zones. Two separate investigations were carried out:

- A separate random effects model was estimated using the aforementioned nesting structure for every survey year
- A mixed effects model was also estimated with all years pooled together

The study showed that, by investigating the total variance of the random effects, the total variance daily travel distance decreases over time. This may indicate that, at least the population surveyed, is slowly developing increasingly homogeneous behavior over time. Further, the authors also show by calculating the variance partition coefficients (see chapter 5) at every level within the hierarchy, that over 90% of the variation in travel distance may be attributed to variations between individuals within households and variations between households. The study, although unique, does not correct for the differences in sampling frame and the different survey methods adopted across the four surveys, which may lead to biased estimates over time (Ampt & Stopher, 2006).

Another example of a study leveraging mixed effects models and survey data to understand travel behavior was conducted by Borgoni et al. (2002). A one-off cross-sectional survey (Austrian micro-census) was adopted as the data source for the analysis. A multilevel logit model (generalized linear mixed model or GLMM) was used to investigate the decision of car ownership (binary variable with 1 equating car ownership and vice versa) based on household and regional attributes (Borgoni, et al., 2002). Individual level choices were nested within regions to create the multilevel structure. The authors investigated the effect of the addition of micro-level (lowest level in the hierarchy) variables on the regional variance component, along with the inclusion of population density as a macro-level variable (highest level in the hierarchy, i.e. region). The authors concluded that household level characteristics and car technology variables are important predictor variables for determining car ownership. These variables, along with population density, helped reduce the regional heterogeneity by observing the decline in the variance partition coefficient of the regions level after the addition of the study variables (Borgoni, et al., 2002). Nevertheless, the authors do not incorporate the household structure in the multilevel framework. Clustering individuals within households can potentially alter the variance partition coefficient pertained to the between-region differences. Further, the nature of the survey data used (cross-sectional survey) prevents the potential of investigating the variation attributed to different time periods, such as months, seasons or years.

Another seminal piece of work was completed by Goulias (2002). Goulias used a panel dataset, the Puget Sound Transportation Panel (PTSP), conducted in California to estimate a set of four correlated activity based multilevel models (Goulias, 2002). The four multilevel models investigated individual choices in time allocation to maintenance, subsistence, leisure and travel time. A three-level nested hierarchy was exploited with occasions of measurements as the lowest level, individuals as the second and households as the third. The joint and multivariate correlation structure of the dependent variables, along with the flexibility offered via the use of mixed effects models, allowed for the investigation of three key factors: the behavioral context of individuals, heterogeneity of behavior and longitudinal variation of time allocation. The author's key finding is that the household level variance was more than one-third of that of the individual level, and thus was considered significance. Further, the author also concluded that clear evidence exists of non-linear dynamic behavior in time-allocation. None of the above have combined the flexibility of mixed effects or multilevel models with continuous travel survey data.

In conclusion, for a continuous survey, a multilevel modelling structure is recommended to predict trip rates and depict travel behavior using continuous data, while correlating successive time periods. Such models can capture fixed as well as random effects of different elements, and hence is also known as mixed-effect models. The fixed-effects, i.e., the variables usually estimated in a regular regression model (household size, number of vehicles, income, etc.) can be estimated while accounting for the random effects, per spatial unit (i.e. zone) or time period (e.g.

year). A unique slope and/or intercept may be generated for variables of interest for each time period and/or each spatial unit. Such a modelling framework can not only identify the development of trends over time, but can also identify the variables that influence these trends. Other examples of time-series modelling frameworks are simply less dynamic in comparison with multilevel models, such as growth or distributed lag models (Steele, 2011). This is because simple time series models do not capture the spatial correlation of trip generation. A more detailed and mathematical explanation of multilevel/mixed effects models may be found in chapter 5.

3.6 Estimating Mode Choice Models from Continuous Surveys

A significant proportion of travel behaviour research is centred on the estimation of discrete choice models. To be considered as a viable substitute, continuous or repeated cross-sectional data must lend itself towards the formulation of mode choice and trip behaviour models. This section will address the subject of mode choice models, albeit shortly, while providing recommendations for how to incorporate the data needs of such models using continuous survey data.

Recently, Habib et al. used TTS data from 1996, 2001, and 2006 to test the viability and robustness of using repeated cross-sectional data for estimating mode choice models (Habib, et al., 2014). The authors proposed a nonlinear (polynomial or logarithmic) function of time to capture the evolution of consumer preferences. A pooled data model specification was suggested. The model captured the error structure and the scale parameter of an entropy based heteroscedastic Tree Extreme Value (hTEV) model over time. Such a specification was stated to capture the temporal evolution of mode preferences. The proposed model considered 1996 as the base year. The authors concluded that the pooled model outperformed year-specific models in terms of model transferability. The pooled model may also be more robust for long-term forecasting (Habib, et al., 2014).

Further, an example of using repeated cross-sectional data for activity generation may also be found in the literature. The paper authored by Salem and Habib (2015) pooled 3 waves of TTS data to develop a meta-model of activity generation processes. The authors concluded that the use of multiple repeated cross-sectional data improved temporal transferability of the model significantly (Salem & Habib, 2015).

However, it is difficult to find the statistical approach adopted by regions around the world in preparing data for modelling, and the modelling approach that can make the best use of continuous data. The Bureau of statistics and Analytics in Sydney Australia, for instance, uses continuous data for region-wide mode choice estimation and long-term forecasting. There, continuous data are pooled to ensure a sufficient sample for modelling purposes. The demand models are updated every five years, in line with the census (Bureau of Transport Statistics, 2013). Nevertheless, the method of pooling and estimation is not clear. Therefore, based on the knowledge obtained from the examples above, an innovative approach is presented below.

It is proposed that transportation authorities adopt the following method to estimate/update its travel model. First, the data are prepared for modelling by pooling over a specific time period (for example, if a complete model run is to be executed every five years, then the data should be pooled over a five-year period). It is recommended that the fall period of every year is solely used for pooling to better represent a “typical” work day. For a more comprehensive method of pooling continuous data for model estimation, please refer to chapter 2. After that, for executing consecutive model runs (e.g. model run 1 in year 5 and model run 2 in year 10), a scale parameter can be added to capture the temporal variation between the datasets.

3.7 Chapter Summary

In this chapter, a detailed literature review concerning the state of practice and use of continuous surveys was presented. Continuous surveys were compared to their cross-sectional and panel counterparts while listing the advantages and disadvantages of each. The issue of sample size was expanded in the context of continuous surveys, along with proposing methods for the weighting, validation, and pooling of data. Also, case studies of three unique continuous surveys were discussed in detail. Further, light was shed on model development using continuous data. It was determined that continuous data has been, although rarely, used for training a four stage model. That said, continuous data seems to have potential in helping transportation authorities in depicting travel behavior over time. This is due to the fact that the data itself is collected on an ongoing basis, capturing the trip decisions of individuals and households every day, week, month, season and year. In an effort to better understand the implications of using continuous data for depicting travel behavior, the mixed effects/multilevel econometric framework was presented. The hierarchical structure of the model matches that of a travel survey, where the clustering of trips occurring within the same time period or originating from the same zone, mode or household is taken into effect. Moreover, the use of a mixed-effects modelling framework allows for the partitioning of the dependent variable's variance. Thus, the variance contribution of each level in the model hierarchy may be examined. This paves the way for a very important empirical study, where the capacity of continuous survey data in capturing the temporal rhythms of travel behavior is investigated.

The next few chapters focus on the empirical study mentioned above. Chapter 4 discuss the empirical exercise to be conducted. In addition, it presents the mathematical form of the mixed effects econometric framework in detail, while also expanding on its variance partitioning capabilities. After that, chapter 5 presents the Montreal Household Continuous Survey dataset; the dataset used for the empirical investigation. Following chapter 5, the modelling results are then displayed in chapter 6. There, the capacity of continuous data in capturing temporal travel behavior will be identified at different levels (e.g. individual, household, spatial, modal, etc). Chapter 7 concludes the thesis.

4 Methodology

In this chapter, the methodology behind the empirical exercise investigating the capacity of continuous surveys to depict temporal rhythms of travel behavior is discussed. The mixed effects model econometric framework for predicting continuous outcomes is first explained. This type of mixed effects model constitutes the bulk of research to be conducted. In total, six groups of models were estimated:

1- A group of mixed effects models with individual level observations; the chosen dependent variable was the logarithmic transformation of travel distance
2- A group of mixed effects models with household level observations; the chosen dependent variable was the logarithmic transformation of travel distance
3- A group of mixed effects models with regional level observations; the chosen dependent variable was numbers of trips generated per region per temporal variable
4- A group of mixed effects models with trip level observations; the chosen dependent variable was the logarithmic transformation of travel distance
5- A group of mixed effects models with aggregated modal level observations; the chosen dependent variable was the logarithmic transformation of travel distance
6- A group of mixed effects models for aggregated walking and cycling trips; the chosen dependent variable was the logarithmic transformation of travel distance for one set of models, and the logarithmic transformation of trip counts for another set

Within every group of modelling exercises, various temporal variables were tested as random effects to investigate their contribution to the total variance of the dependent variable through variance partition analysis. Mainly, the temporal variables selected for analysis were season, season by year, month, month by year and year. The dataset and variables used, their description and the procedure followed to clean and prepare the data, can be found in the next chapter.

The multilevel econometric framework for predicting discrete outcomes (known as generalized linear mixed effects models or GLMM) is also explained in this chapter (for binary outcomes). An exercise is conducted at the end of chapter 6 to display the use of such a model. Nevertheless, the focus of this thesis is on understanding the temporal evolution in travel behavior using continuous outcomes only (e.g. trip distance).

The use of mixed effects models attempts to answer one of the research questions investigated in this thesis. That is, is the time period component of a mixed effects model estimated using a continuous survey imperative to the understanding of the factors affecting the overall variation in total trip distance or trip generation, and the use of a hierarchical approach to model travel behavior.

All models were estimated in **R** using the lme4 package.

4.1 Linear Mixed Effects Model

In a standard continuous survey, such as the Montreal continuous survey, respondents were interviewed within households, which were randomly sampled from regions at different time points. Therefore, it is logical to assume that the collected data has an inherent nesting structure. The appropriate methodology to analyze hierarchically nested data is by using a mixed effects model (Rabe-Hesketh & Skrondal, 2012). A mixed effects model attempts to describe the contextual effect of the data while accounting for the variation in the dependent variable originated from multiple levels (Goulias, 2002). Further, a mixed effects model handles random effects. That includes the grouping of observations under higher levels (or clusters) such as the grouping of individuals under households. The act of clustering observations within groups leads to correlated error terms. Treating clustering as a nuisance, as in simple regression, leads to biased estimates of parameter standard errors (Garson, 2013). This can lead to mistakes in interpreting the significance of coefficients. Figure 4-1 shows the nested hierarchy of the survey data.

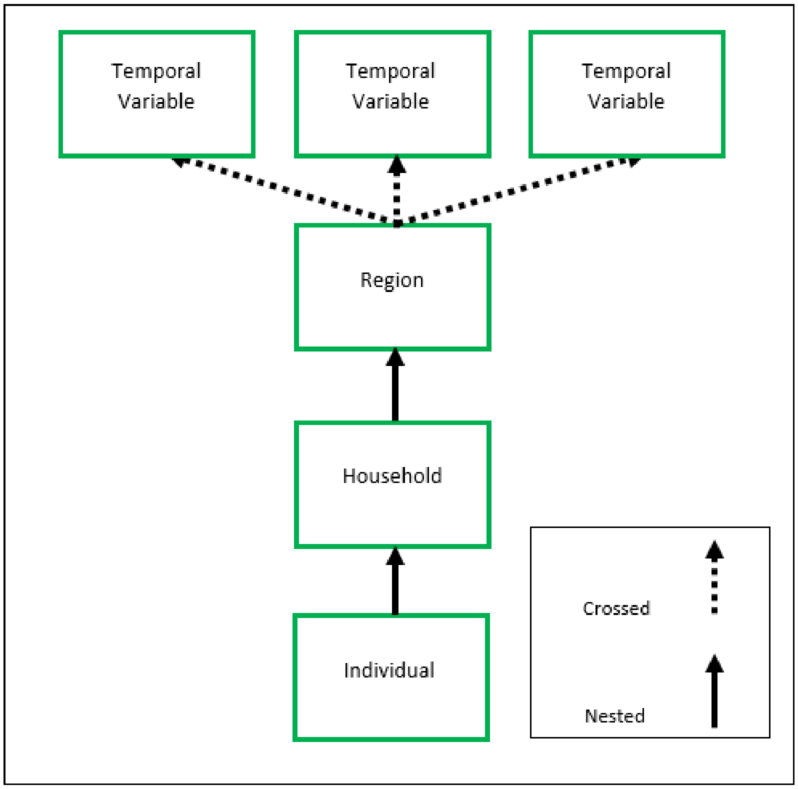

Figure 4-1 Nested Hierarchy of Mixed Effects Model

The figure shows individual respondents nested in households and households nested in their respective regions, as expected. Usually, individuals belong to a single household and households can only be located in one spatial area. On the other hand, the figure shows regions crossed with time periods. This is because data were collected from all regions at continuous time points. In other words, no region belongs to a single time point only, rather the survey design ensured a distributed sampling effort. It is important to recognize the cross-classified structure of the model, for applying a model to nested regions in time points can seriously bias standard errors of parameters and variance component estimates - an important factor in this thesis (Garson, 2013).

To understand a mixed effects model with a structure similar to that displayed in Figure 4-1, it is convenient to first start with a simple two-level hierarchy. A two-level mixed effects model may be expressed in the following form (Scott, et al., 2013):

$$y_{ij} = \beta_0 + u_j + e_{ij}, \quad i = 1, \ldots, N, \quad j = 1, \ldots, J \qquad (23)$$

where y_{ij} is an n x 1 vector of random variables representing the observed value for individual *i* nested in household (group) j. The term u_j is called the group random effects. It is an independent error term (or group effect) assumed to follow a normal distribution of mean 0 and variance σ^2. The individual residuals e_{ij} also represents an independent error term assumed to follow a normal distribution of mean 0 and variance σ^2. Adding explanatory variables is fairly simple:

$$y_{ij} = \beta_0 + \beta x_{ij} + u_j + e_{ij}, \quad i = 1, \dots, N, \quad j = 1, \dots, J \qquad (24)$$

Where β is an n x q matrix of regressors; it represents the coefficient for x_{ij}. The two level notation can be expanded to form a three level mixed effects model, where individual *i* is nested in household *j* and region *k*:

$$y_{ijk} = \beta_0 + u_j + u_{jk} + e_{ijk} \qquad (25)$$

$$i = 1, \dots, N, \quad j = 1, \dots, J, \quad k = 1, \dots, k \qquad (26)$$

Here, u_{jk} is the effect of household *j* nested in region *k*. It is also an independent error term assumed to follow a normal distribution of mean 0 and variance σ^2. To represent the crossed effects, the model notation maybe denoted as follows:

$$y_{ijkt} = \beta_0 + u_j + u_{jk} + u_{jt} + e_{ijkt} \qquad (27)$$

$$i = 1, \dots, N, \quad j = 1, \dots, J, \quad k = 1, \dots, k,, \quad t = 1, \dots, t \qquad (28)$$

The above notation adds another random effect u_{jt}. The subscript of the effect implies the nesting of households *j* in time periods *t*[34]. The absence of the subscript k in the additional random term denotes that the effects u_{jk} and u_{jt} are crossed. That is, region *k* is crossed with time period *t* (Scott, et al., 2013). It is important to note that effects u_{jk} and u_{jt} are no longer independent of each other, rather they have a bivariate normal distribution with zero means and an unstructured 2x2 covariance matrix (Rabe-Hesketh & Skrondal, 2012).

---

[34] Every household was only surveyed once at a specific point in time, and thus can only be nested in time

4.1.1 Variance Partition Coefficient Analysis

Following specification and model estimation, the VPCs of each grouping level were calculated using the following formula (Rabe-Hesketh & Skrondal, 2012):

$$\frac{\sigma_u^2}{\sigma_T^2}, \text{ where } \sigma_T^2 = \sigma_j^2 + \sigma_{jk}^2 + \sigma_{jt}^2 + \sigma_{ijkt}^2 \qquad (29)$$

The VPC ranges from 0 to 1. If the VPC of a level is 0, no between-group differences exist. If the VPC is equal to 1, no within group differences exist (Fiona, 2008). The VPC measures the proportion of total variance in the dependent variable that is due to the differences between groups. For a simple mixed effects model[35], the VPC is equal to the intra-class correlation (Fiona, 2008). The intra-class correlation is the correlation between the selected dependent variable of two individuals from the same group (e.g. household).

To illustrate with an arbitrary example, a VPC of 0.2 for time periods implies that 20% of the variation in the dependent variable is between time periods and 80% is within. The intra-class correlation is also equal to 20%.

In this investigation, different time periods (months, seasons, and years) will be tested for significance, and their VPC, along with that of other groups, will be calculated accordingly. This exercise is essential to understand the reasons behind the variation in trip behavior in general. A log likelihood ratio test will be used to identify the significance of the grouping factors (Rabe-Hesketh & Skrondal, 2012).

4.2 Generalized Linear Mixed Model

It is quite common in transportation research to estimate models with a binary or discrete outcome. For instance, it may be of interest to investigate the factors influencing the choice of "active" commute via walking and cycling versus all other modes of transport. As discussed previously, the collected data are likely to inherent a nested structure, with trips originating from a set of artificial zones for example. In this case, trips or individuals nested in a specific zone or

[35] A simple mixed effect model in this context is one with no random coefficients

region may exhibit correlated behavior, as trips originating from zones with a high score on the mixed land use score are more likely to fall under the “active” transportation label while trips originating from suburban areas are more likely to be auto-dependent. Thus, a multilevel modelling structure may be desirable where random effects (i.e. grouping factors) are added to account for correlated error terms within nests. If clustering is treated as a nuisance, as in a regular binary logit regression, biased estimates of parameter standard errors can ensue. Further, probabilities for the success of an event (e.g. walking or cycling trip) may be calculated at different levels (e.g. trip or spatial level).

A multilevel model for a discrete outcome is referred to as a generalized mixed effects model (GLMM). The following section explains one of the most commonly used GLMM for discrete data, the multilevel binary logit model. A two-level random intercept binary logit model is presented for simplicity.

4.2.1 Simple Binary Logit Regression Model

The general form of the model with one explanatory variable may be represented as (Steele, 2011):

$$\pi_i = F(\beta_0 + \beta_1 x_i) \tag{30}$$

This is equivalent to the expected value of the mean of a binary logit regression. The corresponding model for the outcome y_i becomes:

$$y_i = \pi_i + e_i = \beta_0 + \beta_1 x_i + e_i \tag{31}$$

The *F* in equation 30 is the transformation function or, usually, the cumulative distribution function chosen which maps the probability π_i between negative and positive infinity. The choice of distribution adopted for this study is a logistic function (Fiona, 2011). To obtain a linear in parameters transformation, the inverse of the function *F* is taken. This is known as a generalized linear model.

$$F^{-1}(\pi_i) = \beta_0 + \beta_1 x_i \tag{32}$$

The left-hand side of the model remains nonlinear and is called the link function, as it links π_i to the explanatory variables. The simplest link function is the identity link, which does not alter π at all $F^{-1}(\pi) = \pi$. The sum of the aforementioned parts is called a binary logit model.

If we assume z = $\beta_0 + \beta_1 x_i$. Then, considering the logistic transformation of the variables:

$$\pi = F(z) = \frac{\exp(z)}{1+\exp(z)} \qquad (33)$$

Re-arranging the formula gives the following generalized linear model:

$$\log\left(\frac{\pi}{1-\pi}\right) = z = \beta_0 + \beta_1 x_i \qquad (34)$$

The left-hand term is referred to as the log odds or the logit. The odds ratio may be obtained by removing the log function. That is, by taking the exponential of the right-hand side. Another more familiar way of expressing formula is:

$$\log\left(\frac{p}{1-p}\right) = z = \beta_0 + \beta_1 x_i \qquad (35)$$

If the odds ratio is greater than 1, the odds of the event increase and vice versa. It is also worth noting that the mean or expected value of the outcome y_i is $E(y_i) = \pi_i$.

4.2.1.1 Interpretation of coefficients

The coefficients of a binary logit model are relatively simple to explain. The equation below is the exponential form of equation 4.

$$\frac{\pi}{1-\pi} = \exp(\beta_0 + \beta_1 x_i) \qquad (36)$$

Expanding equation 6 leaves us with:

$$\exp(\beta_0 + \beta_1 x_i) = \exp(\beta_0)\exp(\beta_1 x_i) \qquad (37)$$

It can be seen that adding coefficients to a binary logit model will induce a multiplicative effect. Now, let us consider replacing x by x+1. The resulting equation will be:

$$\exp(\beta_0 + \beta_1[x_i + 1]) = \exp(\beta_0)\exp(\beta_1 x_i)\exp(\beta_1) \qquad (38)$$

It is evident that a 1-unit increase in x has multiplied the odds that y = 1 by $\exp(\beta_1)$. That is, a 1-unit increase in x results with the odds of a "successful" event increasing by a factor of $\exp(\beta_1)$ (Steele, 2011).

4.2.2 Multilevel Binary Logit Model

Consider a two-level structure with *n* individuals (level 1) are nested in *j* regions (level 2). That is, n_j individuals reside in region *j*. The response for individual/trip *i* in region *j*, or any other group for that matter (e.g. household, season, year, etc.), is denoted as y_{ij}, whereas the individual level explanatory variable is denoted as x_{ij}. Thus, assuming one explanatory variable, the following multilevel equation can be obtained (Steele, 2011):

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + u_j + e_{ij} \qquad (39)$$

Where the level 2 residual u_j (also known as the group effect) is assumed to be independent and normally distributed with mean 0 and variance σ_u^2. On the other hand, the level 1 residual e_{ij} is assumed to follow a logistic distribution with mean 0 and σ_e^2. In other words, σ_u^2 and σ_e^2 are regarded as the between group and within group variances, respectively (Steele, 2011). Consequently, the general and generalized linear forms of the model will be:

$$\pi_{ij} = F(\beta_0 + \beta_1 x_{ij} + u_j) \qquad (40)$$

$$F^{-1}(\pi_{ij}) = \beta_0 + \beta_1 x_{ij} + u_j \qquad (41)$$

Where *F* inverse is taken to be the inverse of the cumulative distribution function of the logistic distribution. It may also be replaced by the log-odds (for y = 1):

$$\log\left(\frac{\pi_{ij}}{1+\pi_{ij}}\right) = \beta_0 + \beta_1 x_{ij} + u_j \qquad (42)$$

Effectively, β_0 may be interpreted as the overall intercept, or the log-odds that y = 1 when both x = 0 and u = 0. The intercept for a given group is given by $\beta_0 + u_j$, which may be higher or lower than the overall intercept depending on the value of u_j. The level 1 explanatory variables are interpreted the same way as in a regular binary logit model, while holding $u_j = 0$.

4.2.2.1 Predicting Probabilities

We can calculate the probabilities of an individual or trip *i* in group *j* by substituting the estimates of β_0, β_1, and u_j.

$$\pi_{ij} = \frac{\exp(\widehat{\beta}_0 + \widehat{\beta}_1 x_{ij} + \widehat{u}_j)}{1 + \exp(\widehat{\beta}_0 + \widehat{\beta}_1 x_{ij} + \widehat{u}_j)} \tag{43}$$

Further, we can also make predictions for the 'typical' individual or trip. Nevertheless, selecting the value for u_j in this case proves to be a more complicated process. Two main methods may be found in literature, including integrating out u_j or averaging over simulated values. As estimating GLMMs is a meager objective in this thesis, providing a detailed explanation on predicting probabilities from multilevel structures is outside the scope of this chapter. Nevertheless, a more detailed explanation may be found in (Steele, 2011).

4.2.2.2 Calculating Variance Partition Coefficients

Model 39 in section 4.2.2 may also be written in a latent linear response form:

$$y_{ij}^* = \beta_0 + \beta_1 x_{ij} + u_j + e_{ij}^* \tag{44}$$

The unobserved y_{ij}^* is related to the observed y_{ij} through the following relationship (Steele, 2011):

$$y_{ij} = \begin{cases} 1 \; if \; y_{ij}^* \geq 0 \\ 0 \; if \; y_{ij}^* < 0 \end{cases} \tag{45}$$

The threshold cut point of zero, defining the relationship between y_{ij}^* and y_{ij}, is arbitrary and can take on any number. Indeed, the above model is also known in the field of economics as a threshold model (Steele, 2011).

In equation 44, e_{ij}^* is the level 1 residual with mean zero and variance σ_{e*}^2. Nevertheless, since y_{ij}^* is unobserved, it is necessary to set a scale which is achieved by fixing σ_{e*}^2. Since the assumed distribution for the model is the logistic distribution, σ_{e*}^2 is equal to $\pi^2/3$ or 3.29 (Steele, 2011). As previously discussed, the level 2 variance σ_u^2 is independent of σ_{e*}^2 and normally distributed. Therefore, the VPC equation presented in section 4.1.1 for mixed effects models predicting a continuous outcome still stand:

$$VPC = \frac{\sigma_u^2}{\sigma_u^2+\sigma_{e*}^2} \qquad (46)$$

Here, the VPC is interpreted as the proportion of variance in the propensity to be in response category 1 that is due to differences between groups. To illustrate with an arbitrary example, a VPC of 0.2 for time periods implies that 20% of the residual variation in the propensity to be in response category 1 is attributable to unobserved time period differences. This interpretation stems from the fact that as, level 1 explanatory variables are added, the level 1 residual variance σ_{e*}^2 does not decrease (since it is fixed). Consequently, to adjust for the addition of explanatory variables, the proportion of the level 2 variance as compared to the level 1 increases (Steele, 2011). The ratio of the level 2 variance to its level one counterpart measures the proportion of the total residual variance that is due to between-group variation.

5 Travel Survey and Dataset Description

At the end of the 2008 cross-sectional Montreal OD survey, an experimental continuous origin-destination survey was conducted by AMT. The survey started in January 2009 and ended in December 2012. Data were collected on a continuous basis without replacement. That is, no household was sampled twice. The overarching goal was to add value to the regional Montreal cross-sectional 4-year surveys, conducted in 2008 and 2013 (Tremblay, 2014). At that time, AMT was looking for a way to monitor the evolution in travel behavior over time and space. Therefore, a pilot continuous survey was implemented to investigate the potential of such data in capturing changes in travel behavior.

The survey was carried out in a similar fashion to that of Sydney; i.e. in three waves every year (Peachman & Battellino, 2007). Residents of the Montreal Metropolitan Area were only surveyed on weekdays, including weekdays that corresponded with provincial holidays. Interviews were conducted using CATI system, the same CATI tool that was used in the 2008 large-scale household travel survey. The 2008 questionnaire was unadjusted for the continuous survey except for the addition of some new questions on disability mobility, auto availability and respondent arrival time. The addition of the 3 questions cost nearly one additional minute on average interview time. The final results were expanded based on the 2011 census.

The sampling method of the continuous Montreal survey was a hybrid of cell phone, land-line and web-based survey tools (Tremblay, 2014). The planning agency, in an attempt to capture households with no landlines integrated the cell phone based sample. Both a validated cell phone list and random digit dialing was used. The cell-based sample proved to be quite young with most individuals lying in the lower income, no car, and no kids demographic with a preference for active and/or transit mobility.

A postal address sampling frame was employed to conduct the survey (Tremblay, 2014). The addresses in the list were validated against the current list of landline-based households. Households that happened to be on both lists were taken out.

Approximately 15,000 households were surveyed per year. On a typical week, some 250-400 households were surveyed, amounting to 14,400 households in the first year of the survey, and

16,000 to 16,700 for the other three years. The sample size was determined by splitting the typical 4% to 5% cross-sectional survey over a 5-year period. In other words, the total sample surveyed was 63,359 households, which is equivalent to the total number of households surveyed in a 5-year transportation plan. Overall, the total number of individuals surveyed was 152,157. No official results were published after the conduct of the survey. Some analyses were reported, namely the study of changes in cycling levels, but there was no systematic modelling of travel behavior using the data. The data were collected for 8 regions in the Montreal Metropolitan Area. Table 5-1 lists the regions names and numbers as coded in the survey. A map of the Montreal Metropolitan Area is also provided with the regions outlined in Figure 5-1.

Table 5-1 List of Regions by Name, Sample Size, and Population

Region Number	Region Name	Sample Size	Region Population[36]	Sampling Rate
1	Montreal (center-ville)	2,521	72,633	3.47%
2	Montreal (center)	36,874	974,263	3.78%
3	East Montreal	10,967	305,717	3.59%
4	West Montreal	18,396	501,803	3.67%
5	Rive-Sud	14,079	385,535	3.65%
6	Laval	13,614	368,707	3.69%
7	North Couronne	27,453	712,588	3.85%
8	South Couronne	26,986	618,516	4.36%

[36] Population figures are from the 2008 OD survey (Agence métropolitaine de transport, 2008)

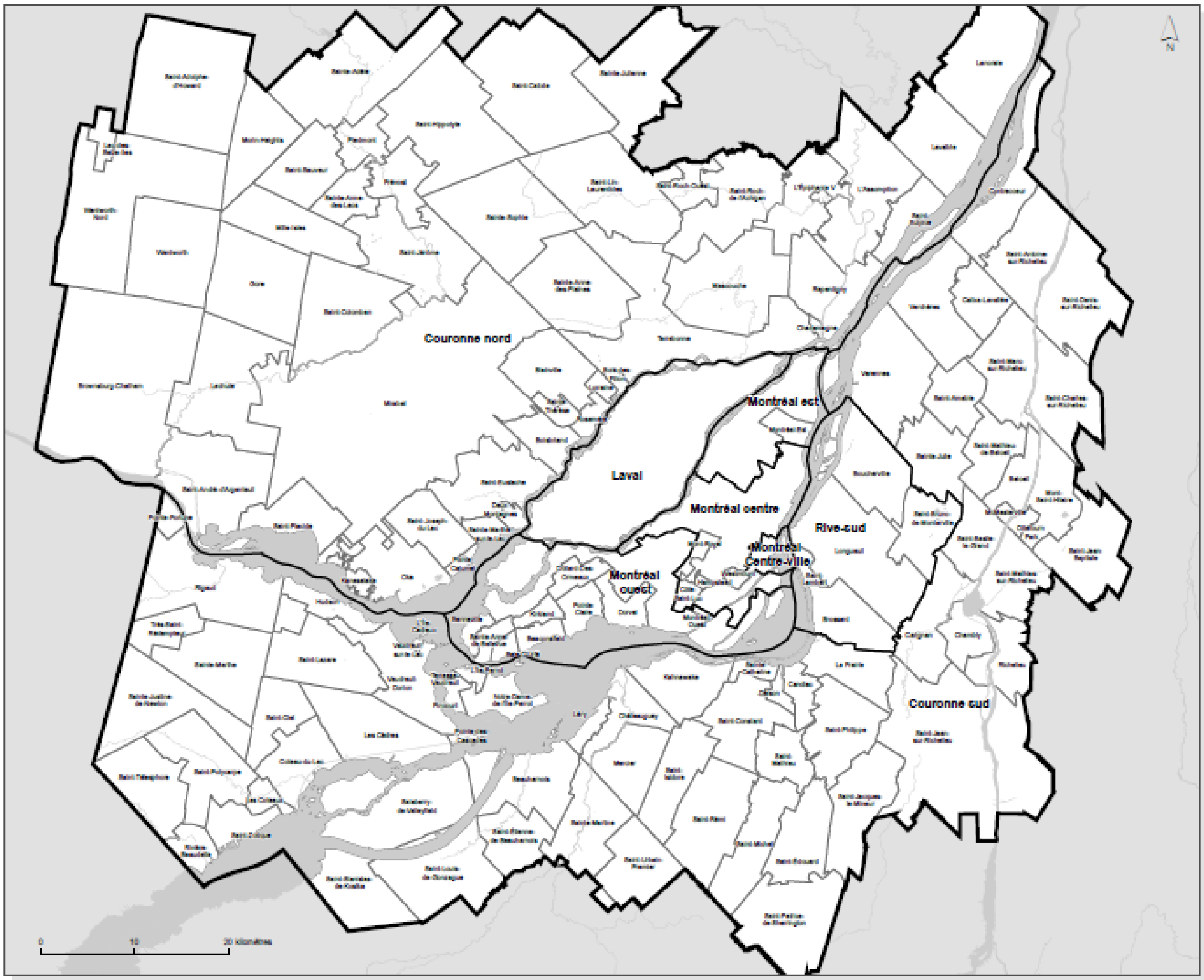

Figure 5-1 Map of the Montreal Metropolitan Area

Every single person and household within the dataset was designated a unique identification number. Household socio-demographics were collected as part of the survey. These include variables such as number of persons in a household, average household income, number of children in a household and number of vehicles. Individual characteristics were also obtained such as age, availability of a driving license, gender, number of trips conducted on the day of the survey, the mode used for each trip and the total distance and duration of trips conducted. Furthermore, the day, week number, month and year of that which the individual and his respective household were coded. An additional column titled “Season” was added to the dataset, where the season was identified based on the month of the year the survey was conducted in.

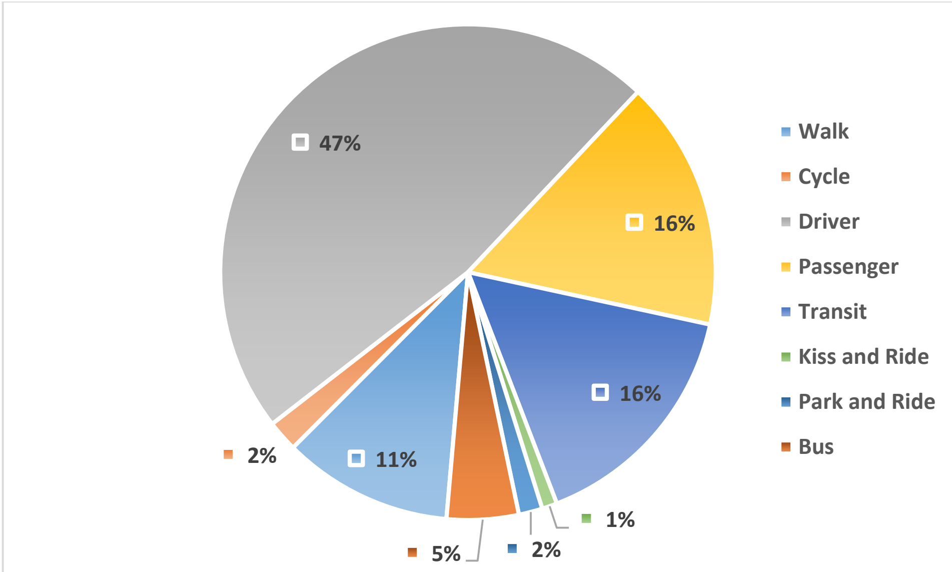

Figure 5-2 Percentage of Mode Share in Montreal Continuous Survey

The mode of every individual trip reported by survey respondents was also included in the dataset. Namely, trips were identified as either walk, cycle, drive, passenger, transit (with the exclusion of bus trips), kiss and ride, park and ride or bus trips. Most of the trips were recorded as either driver or passenger (63%), while 13% of total trips were labelled as either walk or cycle. The remaining 24% of trips belonged either fully or partially to the public transit category. The trip count, distance and time by every mode was recorded. Figure 5-3 presents a disaggregate distribution of all trips conducted on the day the respondents were surveyed (numbers were rounded to the nearest 1%).

5.1 Data Cleaning and Preparation

After completion of the survey, the responses were validated to limit the presence of erroneous records in the dataset. The resulting dataset contains all trips, their related attributes as well as data on individuals and households. While some variables were readily available for modelling, others required preprocessing such as trip chain identification and duration estimation. Other databases were fused with the survey dataset; namely data from Environment Canada on daily weather conditions from the international airport sensor (snow, rain, average temperature), and fuel price from the Régie de l'énergie du Québec.

The dataset was then prepared for modelling. Holidays were removed from the dataset so as to capture trip distance variation on an “average” workday. The total number of records removed was 958. After that, records with missing values were deleted, bringing down the total number of surveyed individuals to 148,992. Respondents who answered a survey question by “I refuse to answer” or by “I don’t know”, or records with missing values were also removed.

A description of the available variables in the dataset may be seen in Table 5-2 below. Table 5-3 provides summary statistics.

Table 5-2 Definition of Variables in Dataset for Econometric Investigation

	Variable	Definition	Variable Type
Trip Attributes	tripdu	Total duration of a respondents' trip chain	Continuous
	tripd	Total distance of a respondents' trip chain	Continuous
	tripr	Total number of trips in a respondent’s trip chain	Count
Person Attributes	age	Age in years	Continuous
	driv_lic	Driving license = 1 if respondent carries a driving license; = 2 otherwise	Binary
	gender	Gender of respondent = 1 if male; = 2 if female	Binary
	occ_status	Occupation Status of respondent; 1 = Full time worker; 2 = Part time worker; 3 = Student; 4 = retired; 5 = work at home	Categorical
Household Attributes	nb_child	Number of children under 16 years of age in a household	Continuous
	hhsize	Number of persons in a household	Continuous
	carown	Number of cars owned by household	Continuous
	income	Household income 1= 0$ - 20 000$; 2 = 20 000$ - 40 000$; 3 = 40 000$ - 60 000$; 4 = 60 000$ - 80 000$; 5 = 80 000$ - 100 000$; 6 = 100 000$+	Categorical
Other Variables	rainday	Rainday = 1 if it rained on the day of the survey; = 0 otherwise	Binary
	snowday	Snowday = 1 if it snowed on the day of the survey; = 0 otherwise	Binary

	Population	Number of residents per municipal sector	Continuous
	fuelprice	Fuel price on the day of the survey	Continuous
Spatio-Temporal Variables	region	Region address of Household: based on 8 large regions	Categorical
	Municipal Sector	108 zones representing municipalities or districts	Categorical
	Year	Year of survey	Categorical
	Season	Season of survey	Categorical
	month	Month in year of survey	Categorical
	no_week	Week in year of survey	Categorical
	dow	Day of week in year of survey	Categorical
	Season by Year	Season of year (e.g. fall 2011, winter 2011, spring 2011, summer 2011, fall 2012, etc.)	Categorical
	Month by Year	Month of year (e.g. Jan 2011, Feb 2011, March 2011, etc.)	Categorical

Table 5-3 Summary of Descriptive Statistics

	Variable	Unit	Min	Max	Range	Median	Mean	Std Dev
Trip Attributes	tripdu	min	0	1410	1410	445	365	269.57
	tripd	Km	0	354	354	10	18	20.78
	tripr	N/A	0	22	17	2	2.4	1.69
Person Attributes	age	years	0	99	99	42	39.96	22.31
	driv_lic	N/A	1	2	1	N/A	1.29	N/A
	gender	N/A	1	2	1	N/A	1.52	N/A
Household Attributes	nb_child	N/A	0	8	8	N/A	N/A	N/A
	hhsize	N/A	1	21	20	3	3.07	1.4
	carown	N/A	0	14	14	2	1.61	1.03
Other Variables	rainday	N/A	0	1	1	N/A	0.37	N/A
	snowday	N/A	0	1	1	N/A	0.13	N/A
	fuel.price	$	81.5	146.9	65.4	115.5	118.03	16.69
	Population	N/A	962	126600	125638	55530	55370	30846

5.1.1 Data Preparation for Individual Level Modelling

It was noticed that approximately 17% of the remaining respondents reported zero trips on the day they were surveyed. Therefore, to avoid floored residuals, individuals who didn’t conduct any trip, or conducted a trip of less than 0.5 km in distance, were removed. This provides for a more homogeneous group for analysis. The final dataset has 88,156 individual records.

5.1.2 Data Preparation for Household Level Modelling

The total trip distance per household was calculated from the survey dataset. Household level attributes were also aggregated accordingly. Further, households with a total of zero trips were not included in the analysis. Indeed, every row in the resulting dataset constituted a household. The final dataset has 42,895 household records.

5.1.3 Data Preparation for Spatial Level Modelling

The total number of trips per spatial unit (region or municipal sector) per time period were aggregated. No individuals were excluded.

5.1.4 Data Preparation for Trip Level Modelling

The survey dataset was converted from wide to long format based on the trip distance of each trip conducted by survey respondents. That is, every row was a trip, rather than an individual. The grouping factors (random effects) considered were mode, spatial unit (either region or municipal sector) and time period.

5.1.5 Data Preparation for Modal Level Modelling

The survey dataset was converted from wide to long format based on the trip distance of each trip conducted by survey respondents. That is, every row was a trip, rather than an individual. The trips were then aggregated by mode. Modal, spatial and temporal random factors were included. A separate model was estimated for each combination of random factors.

5.1.6 Data Preparation for Active Modes Modelling

A subset of the dataset in section 5.1.5 that included trips conducted by walking or biking was taken out and used for modelling. A random effects model was then estimated with the log of trip distance as the dependent variable for a set of models, and the log of number of trips by mode for another set of models. The grouping factors (random effects) considered were Mode, region and different time periods. Only region was considered for spatial units due to the small sample size of trips conducted by active modes of transport. That is, the number of trips, or total trip distance covered, by active modes would have been too thinly distributed across different municipal sectors for analysis purposes. A separate model was estimated for each combination of random factors.

6 Results of Mixed Effects Modelling

In this chapter, a series of mixed-effects models (as described in chapter 4) predicting continuous outcomes that act as a proxy for travel behavior (such as trip distance and the number of trips) are estimated. A selection of temporal, spatial, modal and other variables was tested as random effects while calculating their respective VPCs. The objective of this exercise is to identify whether the temporal variables tested as random effects explain a significant proportion of the total variance in the dependent variable. In other words, the aim of the investigation is to determine whether continuous survey data can capture the temporal nature of travel behavior. The modelling exercise is repeated for the individual, household, spatial, trip and modal level. The log likelihood and AIC values for the models can be viewed in the Appendix.

This chapter also extends the use of mixed effects models to predicting binary outcomes. Nevertheless, the focus is on continuous outcomes rather than the later.

6.1 Individual Level Mixed Effects Model

The Montreal continuous survey dataset was used to develop a mixed effects model that investigates the relationship between the natural logarithm of total trip distance covered in a day by a single person and various household and individual attributes. The natural logarithm of the total trip distance was used since trip distance is a non-negative variable (i.e., inherently skewed from the normal distribution). The effect of clustering was taken into account by nesting individuals in households, and households in regions. Regions were crossed with various time periods to investigate the variance contribution of the selected time periods to the total variation in trip distance.

Table 6-1 lists the parameter estimates, t-statistics and confidence intervals. An ANOVA comparison showed that the seasonal model was the best. Thus, only the fixed effects of the season model are presented. For the income variable, income category 1 (0 – $20,000) was used as a base. Similarly, the “other” work category was set as the base for the variable *occupation status*.

Almost all parameters were estimated with the expected signs and were statistically significant at the 95% confidence interval, with the exception of household size. Interestingly, household size was a significant variable until the addition of the region random effect. Thus, it may be that the effect of household size is region dependent, with individuals living further away from the downtown core may be travelling longer distances on a daily basis and vice versa[37].

Table 6-1 Seasonal Individual Level Mixed Effects Model

Variable	Description	Estimate	Std. Error	t-value
(Intercept)	N/A	2.033	0.111	18.311
income2	$20,000 - $40,000	0.133	0.013	10.222
income3	$40,000 - $60,000	0.241	0.014	17.851
income4	$60,000 - $80,000	0.304	0.014	21.03
income5	$80,000 - $100,000	0.359	0.017	21.687
income6	$100,000+	0.41	0.015	26.967
Age	N/A	0.006	0	18.075
Female	N/A	-0.098	0.006	-16.846
occ_status1	Full Time	0.449	0.019	24.033
occ_status2	Part Time	0.185	0.022	8.281
occ_status3	Student	-0.142	0.021	-6.803
occ_status5	Work at Home	-0.212	0.022	-9.828
occ_status6	Retired	-0.09	0.025	-3.533
hhsize	Household Size	-0.004	0.003	-1.323

The income variable, as in all income categories compared to the base category, was statistically significant and positively correlated with total trip distance travelled. This is in line with transportation literature (Meyer & Miller, 2001). Further, women seem to prefer travelling shorter travel distances as the women variable proved to be negatively correlated with the dependent variable (taking men travelers as a base). This may be because women tend to work closer to home (Hanson & Johnston, 2013). An interaction variable consisting of gender and occupation status was tested to determine if this behavior may vary across different employment

[37] The model was re-estimated while eliminating the hhsize variable. All parameter estimates were more or less identical. An ANOVA test was conducted to determine whether the model is better off without hhsize. Nevertheless, the null hypothesis could not be rejected and it was decided to keep the variable.

conditions. Nevertheless, the results proved insignificant and the interaction term was removed from the model.

A significant positive relationship between age and total trip distance was also identified. This is a reasonable conclusion as with age comes more household responsibility, resulting in longer distance travel. Further, full time and part time workers showed a positive correlation with total trip distance as compared to the “other” work category. The survey did not ask whether the individual was unemployed, rather it included an “other” category. Thus, full and part-time workers may well travel more than other non-workers for commuting and other activities. On the other hand, Individuals who work at home alongside retirees and students may choose to travel on shorter trips for leisure, maintenance and subsistence activities (Goulias, 2002). Overall, a working individual (or even a retired man or women) may have a larger spending capacity and thus justifying the feasibility of longer trip making.

6.1.1 Variance Partition Coefficient Analysis

Five mixed effects models were estimated using the same previously described variables, but while varying the time period component. That is, mixed model 1 was assigned “Season” as its time variable, mixed model 2 was assigned “Season by Year”, mixed model 3 was assigned “Month” as its time variable, etc... The objective of including a time period as a random effect is to understand the total variation in the dependent variable – total trip distance travelled in this case – attributed to a specific temporal variable. If the random effect is significant, and the VPC is substantive, then it is safe to say that continuous surveys are more effective than cross-sectional surveys in the sense that the variation of trip behavior over time may be observed. Table 6-2 lists the results of the VPC analysis.

Table 6-2 Individual Level VPC Analysis

Time Period	Cluster	Variance	VPC
Season	Time Period	0.00036	0.04%
	Region	0.09186	9.54%
	Household	0.22563	23.42%
	Residual	0.645399	67.00%
Season by Year	Time Period	0.000842	0.09%
	Region	0.09183	9.53%

	Household	0.22514	23.37%
	Residual	0.6454	67.00%
Month	Time Period	0.000369	0.04%
	Region	0.091807	9.53%
	Household	0.22555	23.42%
	Residual	0.64541	67.01%
Month by Year	Time Period	0.00103	0.11%
	Region	0.091856	9.54%
	Household	0.224984	23.36%
	Residual	0.64536	67.00%
Year	Time Period	0.00038	0.04%
	Region	0.0918	9.53%
	Household	0.225812	23.44%
	Residual	0.645279	66.99%

Interestingly, all time period random effects were proven to be statistically significant via a chi-squared test. Nevertheless, the VPC of every single time period is below 1%. This means that only a small fraction (<1%) of the variance of the total trip distance travelled may be explained by varying time periods. Most of the variation in the total trip distance covered was explained by the differences between individuals (~67%), followed by the variation between households (~23%), and that between regions (~9.5%). The relatively large VPC for households and regions gives support for active research areas in transportation planning that tackle household interactions (Roorda, et al., 2009). Further, the fact that more than 30% of the variation in trip behavior is explained by the different random effects implies that the data exhibits some degree of clustering (Rabe-Hesketh & Skrondal, 2012).

6.2 Household Level Mixed Effects Model

The Montreal continuous survey dataset was used to estimate a series of mixed-effects models that investigate the relationship between the natural logarithm of total trip distance covered in a day by a household and various household characteristics. Similar to the individual-level model, the effect of clustering was taken into account by nesting households in regions. The regions were also crossed with time periods to assess the temporal variability of travel distance on the household level.

Table 6-3 lists the fixed effects chosen along with their parameter estimates, t-statistics and confidence intervals. All variables were shown to be significant with the expected signs. The results show that travel distance is positively correlated with increasing income, car ownership, and household size.

Table 6-3 Seasonal Household Level Mixed Effects Model

Variable	Description	Estimate	Std. Error	t-value
(Intercept)	N/A	1.910648	0.0991	19.28
income2	$20,000 - $40,000	0.320781	0.014214	22.57
income3	$40,000 - $60,000	0.538065	0.015092	35.65
income4	$60,000 - $80,000	0.651359	0.016648	39.13
income5	$80,000 - $100,000	0.743763	0.019633	37.88
income6	$100,000+	0.771728	0.018289	42.2
carown	Car ownership	0.191677	0.005612	34.15
hhsize	Household Size	0.243418	0.003801	64.05

6.2.1 Variance Partition Coefficient Analysis

Five temporal variables were assessed for significance: month, season, year, month by year and season by year. All temporal variables were shown to be significant via an ANOVA test. Contrary to the individual level analysis, the VPCs were calculated for both region and municipal sector spatial units.

The variance contribution of temporal variables to the total variance in total travel distance on the household level was less than 1%. Thus, although statistically a temporal variation exists, the magnitude of that significance is negligible. Table 6-4 provides a summary of the variation contribution of the different temporal variables on the dependent variable, alongside the other random effects. It is evident from the table that approximately 90% of the trip variation in the dependent variable is due to the variation within regions/municipal sectors and between households, with the remaining 9%-to-10% attributed to differences between regions/municipal sectors. Only minor differences may be observed in the VPCs when comparing the region-based models to the municipal sector-based models.

Table 6-4 Household Level VPC Analysis

Time Period	Cluster	Region Variance	Region VPC	Municipal Sector Variance	Municipal Sector VPC
Season	Time Period	0.000321	0.04%	0.0003247	0.04%
	Spatial Unit	0.076363	8.68%	0.0886567	10.21%
	Residual	0.8029	91.28%	0.7791814	89.75%
Season by Year	Time Period	0.00223	0.25%	0.002249	0.26%
	Spatial Unit	0.07707	8.75%	0.089473	10.29%
	Residual	0.80116	90.99%	0.777406	89.45%
Month	Time Period	0.0003724	0.04%	0.0004068	0.05%
	Spatial Unit	0.0764017	8.69%	0.0886413	10.21%
	Residual	0.8027961	91.27%	0.7790549	89.74%
Month by Year	Time Period	0.002449	0.28%	0.002513	0.29%
	Spatial Unit	0.077042	8.75%	0.089387	10.29%
	Residual	0.800837	90.97%	0.777058	89.42%
Year	Time Period	0.002017	0.23%	0.001882	0.22%
	Spatial Unit	0.07745	8.79%	0.089629	10.31%
	Residual	0.801711	90.98%	0.777955	89.48%

6.3 Spatial Level Mixed Effects Model

Unlike individuals and households, a continuous survey dataset is likely to exhibit repeated observations at a spatial unit recorded over time. This is especially true if the spatial unit is large (such as a region). In other words, the continuous dataset on the region level exhibits a panel-like structure. Therefore, a more interesting modelling exercise is to investigate the contribution of various temporal variables to the variation in the total variance of the dependent variable on different spatial units.

A series of random-intercept only models (with the exception of including the logarithm of population for all municipal sector models)[38] were estimated in the region and municipal sector

[38] The region population variable was not made available in the dataset. Thus, it could not be included as an independent variable in the modelling exercise.

level, with data aggregated temporally over seven different time periods: year, day of week, day by year, month, month by year, season and season by year. The dependent variable was chosen to be the logarithm of trip generation, aggregated by region/municipal sector and a temporal variable. All of the temporal random effects mentioned were found to be significant at the 95% confidence interval. Table 6-5 provides a summary of the variance partition coefficient results.

Table 6-5 Spatial Level VPC Analysis

		Region		**Municipal Sector**	
Time Period	**Cluster**	**Variance**	**VPC**	**Variance**	**VPC**
Season	Time Period	0.017787	2.89%	0.01531	25.65%
	Spatial Unit	0.596044	96.92%	0.02824	47.32%
	Residual	0.001127	0.18%	0.01613	27.03%
Season by Year	Time Period	0.025871	4.09%	0.02635	19.63%
	Spatial Unit	0.599652	94.79%	0.03013	22.44%
	Residual	0.007113	1.12%	0.07778	57.93%
Month	Time Period	0.046105	7.15%	0.05675	35.37%
	Spatial Unit	0.592891	91.99%	0.03032	18.90%
	Residual	0.005521	0.86%	0.07339	45.74%
Month by Year	Time Period	0.04018	6.04%	0.0497	15.67%
	Spatial Unit	0.60056	90.25%	0.02905	9.16%
	Residual	0.02469	3.71%	0.23835	75.17%
Day of Week	Time Period	0.003888	0.65%	0.002984	4.87%
	Spatial Unit	0.594501	99.09%	0.027841	45.48%
	Residual	0.001575	0.26%	0.030392	49.65%
Day of Week by Year	Time Period	0.009915	1.61%	0.007831	4.71%
	Spatial Unit	0.599095	97.15%	0.029191	17.57%
	Residual	0.00764	1.24%	0.129124	77.72%
Year	Time Period	0.0066726	1.11%	0.003186	7.24%
	Spatial Unit	0.5945349	98.79%	0.029365	66.72%
	Residual	0.0005903	0.10%	0.011461	26.04%

Approximately 90% to 98% of regional level trip generation variance may be attributed to between-region differences. Nevertheless, the VPC analysis for the region level model provided unique insights on the effect of various temporal variables, and between and within region differences, on trip generation. It can be observed that, on the year level, approximately 1% of the variation in trip generation is to be attributed to between year differences. Almost all of the remaining variance is attributed to between-region differences. Therefore, it can be concluded that no major changes in trip generation occurred over the 4-year period of the continuous survey due to differences in years. The between season and between month VPCs were larger at approximately 3% and 6%, respectively. That is, the variation in trip generation on the region level is increasingly explained by more disaggregate time units. This may be attributed to the fact that seasons and months may differ significantly from one another (weather changes, school year, etc..) affecting travel behavior as opposed to a homogeneous set of years. Nevertheless, the trend does not follow for the between day VPC as weekday day-to-day trip generation may not exhibit significant differences.

On the other hand, the VPC analysis for the municipal sector model yielded much larger time period coefficients with 7% for between year, 25.7% for between season and 35.4% for between month variation. The results indicate that a larger proportion of trip generation behavior can be explained when modelling on a more disaggregate spatial scale. One potential reason may be due to the land use and built environment differences that can be observed when comparing smaller geographic units as opposed to larger ones, influencing the mode of trips selected and the number of trips generated by residing populations. Moreover, a significant proportion of the variance in trip generation is explained by the within municipal sector differences (differences in trip generation between households and individuals for example) with the VPC ranging from 26% to approximately 46%. This is much larger than what can be observed on the region level for, while regional residents may exhibit behavioral differences, the average regional trip generation is potentially more or less the same.

6.4 Individual Trip Level Model

The mixed effects modelling exercise was then extended to investigate the relationship between the logarithm of trip distance and a number of explanatory variables for every individual trip captured by the Montreal Continuous Survey from 2009 to 2012. That is, the multiple trips conducted by an individual were modelled independently. The effect of clustering was also taken into account. Trips were nested in modes, and modes were crossed with regions and time periods. Ideally, the clustering effect of every individual person should be taken into account.

However, adding such a random effect will multiply the complexity of the model leading to a failure in conversion.

Table 6-6 lists the fixed effects chosen along with their parameter estimates, t-statistics and confidence intervals. The seasonal model coefficients were chosen to remain consistent with the table results displayed in section 6.1 and 6.2. The parameter estimates as a result of varying the time component were very similar when compared to the seasonal model. All variables were shown to be significant with the expected signs. Household size was again an exception in this modelling exercise as the parameter estimate produced a negative sign. This may be because as the household size increases, individual trip distance per person may decrease as the chore of travelling is distributed across the many residents of the household. Aside from household size, trip distance increases with income and age, while women seem to travel on shorter trips than their male counterparts.

Table 6-6 Seasonal Trip Level Mixed Effects Model

Variable	Description	Estimate	Std. Error	t-value
(Intercept)	N/A	1.8724	0.249	7.51
income2	$20,000 - $40,000	0.0382	0.01	3.72
income3	$40,000 - $60,000	0.1076	0.011	10.23
income4	$60,000 - $80,000	0.1355	0.011	12.25
income5	$80,000 - $100,000	0.168	0.012	13.56
income6	$100,000+	0.2054	0.011	17.93
Age	N/A	0.0038	0.0003	13.4
Female	N/A	-0.087	0.006	-15.67
occ_status1	Full Time	0.4584	0.011	40.52
occ_status2	Part Time	0.2789	0.015	18.01
occ_status3	Student	0.1655	0.017	9.55
occ_status5	Work at Home	0.1803	0.019	9.33
occ_status6	Retired	0.1571	0.019	8.11
hhsize	Household Size	-0.006	0.002	-2.53

6.4.1 Variance Partition Coefficient Analysis

Five temporal variables were assessed for significance: month, season, year, month by year and season by year. Also, the analysis was conducted for both regions and municipal sectors. All temporal variables were shown to be significant via an ANOVA test, with the exception of the year variable. This indicates that no significant change has happened in the variation of trip distance between years.

The variance contribution of temporal variables to the total variance in trip distance was less than 1%. The results are similar to that of the individual level and household level modelling exercises and are expected since every trip is observed once (no repeated observation per trip). Table 6-7 provides a summary of the variance contribution of the different temporal variables on the dependent variable, alongside the other random effects. It is evident from the table that approximately 60% of the trip variation in the dependent variable is due to the variation between trips and within modes. Also, approximately 35% of the variation in trip distance is attributed to between mode differences, indicating that the choice of travel mode is quite significant to understanding travel behavior. Finally, about 3% of the variation in trip distance is attributed to between-region differences, while between municipal sector differences explain about 7% of that variation. This is in line with the results of previous modelling exercises in this thesis.

Table 6-7 Trip Level VPC Analysis

		Region		Municipal Sector	
Time Period	**Cluster**	**Variance**	**VPC**	**Variance**	**VPC**
Season	Time Period	0.000686	0.05%	0.000666	0.05%
	Spatial Unit	0.04173	3.34%	0.088759	7.03%
	Mode	0.449462	35.92%	0.435268	34.50%
	Residual	0.759269	60.72%	0.737024	58.41%
Season by Year	Time Period	0.000692	0.06%	0.000635	0.05%
	Spatial Unit	0.04182	3.34%	0.08886	7.05%
	Mode	0.448743	35.89%	0.434725	34.47%
	Residual	0.759136	60.71%	0.736926	58.43%
Month	Time Period	0.000696	0.06%	0.000656	0.05%
	Spatial Unit	0.041707	3.33%	0.088687	7.03%
	Mode	0.449362	35.92%	0.435061	34.49%
	Residual	0.759163	60.69%	0.736939	58.42%
Month by Year	Time Period	0.00093	0.07%	0.000862	0.07%
	Spatial Unit	0.041823	3.34%	0.088941	7.05%
	Mode	0.448701	35.89%	0.434487	34.46%
	Residual	0.758894	60.69%	0.736689	58.42%
Year	Time Period	9.26E-06	0.00%	0	0.00%
	Spatial Unit	4.17E-02	3.34%	0.08873	7.04%

	Mode	4.48E-01	35.83%	0.43368	34.42%
	Residual	7.60E-01	60.83%	0.73752	58.54%

6.5 Modal Level Model

Contrary to individual trips, a continuous survey dataset is likely to exhibit repeated observations on the modal level. Therefore, in an attempt to investigate the temporal variation in travel behavior, a series of random-intercept only models were estimated at the modal level. That is, data were aggregated by mode, alongside the commonly used spatial and temporal variables. The modelling exercise was carried out for both regions and municipal sectors, with data aggregated temporally over five different time periods: season, season by year, month, month by year, and year. The dependent variable was chosen to be the logarithm of trip distance.

All of the temporal random effects mentioned were found to be significant at the 95% confidence interval, with the exception of the year random effect in the regional modelling exercise. Table 6-8 provides a summary of the variance partition coefficient results.

Table 6-8 Modal Level VPC Analysis - Distance as Dependent Variable

		Region		**Municipal Sector**	
Time Period	**Cluster**	**Variance**	**VPC**	**Variance**	**VPC**
Season	Time Period	0.03797	0.92%	0.01429	0.39%
	Spatial Unit	0.90423	21.92%	0.38175	10.30%
	Mode	2.41213	58.48%	2.36938	63.92%
	Residual	0.77061	18.68%	0.94114	25.39%
Season by Year	Time Period	0.02567	0.66%	0.01752	0.57%
	Spatial Unit	0.80538	20.76%	0.32297	10.55%
	Mode	2.3217	59.85%	1.87548	61.26%
	Residual	0.72643	18.73%	0.8632	28.19%
Month	Time Period	0.0416	1.03%	0.03959	1.23%
	Spatial Unit	0.8283	20.56%	0.33714	10.48%
	Mode	2.392	59.37%	1.98853	61.79%
	Residual	0.7672	19.04%	0.85298	26.50%
Month by Year	Time Period	0.03473	0.94%	0.02623	1.08%
	Spatial Unit	0.67824	18.43%	0.25832	10.63%
	Mode	2.19074	59.52%	1.29124	53.11%
	Residual	0.77673	21.10%	0.85533	35.18%
Year	Time Period	0.00228	0.06%	0.00553	0.15%
	Spatial Unit	0.88543	24.84%	0.39501	10.84%

Mode	2.19569	61.60%	2.36861	65.00%
Residual	0.48128	13.50%	0.87503	24.01%

The hypothesis in this thesis has been that if a particular variable, such as mode or region/municipal sector, exhibited repeated observations, then the magnitude of the temporal VPC is likely to be significant. That is, a sizable proportion of the total variance of the dependent variable is explained by the temporal random effect. Nevertheless, the results showed that, at least for the modal level modelling exercise, the temporal random effect explains very little (less than 1%) of the total trip distance variance. There may be two main reasons for such a conclusion. The first is that the variance contribution of the temporal variables is overshadowed by the between-mode differences. Indeed, the between-mode differences are attributed between 58% and 65% of the overall variation in trip distance by mode. The other reason may be that travel behavior over the selected time periods is homogeneous. That is, individuals travel the same distance by mode every month, season or year. Intuitively, this explanation may stand for auto and transit users, but is rather difficult to justify for active modes such as walking and cycling. Section 6.6 is devoted to investigating whether temporal variation in trip behavior may be observed for active modes. Here, active modes are defined as either walking or cycling trips (Mahmoud, et al., 2015).

Aside from the between mode differences, the within mode differences were attributed between 13% to 26% of the total variation in modal travel distance. In addition, the between region/municipal sector differences were attributed anywhere between 10% and 25% of the total variation.

It is important to note that the analysis in this section was repeated for (the logarithm of) trip counts by mode as a dependent variable (Table 6-9) to validate the results. However, the aforementioned conclusions were largely similar. Moreover, the mean of the modal trip distance was also considered in place of the total modal trip distance. Still, no significant changes were observed in the VPCs of the temporal variable.

Table 6-9 Modal Level VPC Analysis - Modal Counts as Dependent Variable

		Region		Municipal Sector	
Time Period	**Cluster**	**Variance**	**VPC**	**Variance**	**VPC**
Season	Time Period	0.02978	0.88%	0.01223	0.45%
	Spatial Unit	0.58597	17.22%	0.42041	15.37%
	Mode	2.16864	63.75%	1.72937	63.23%
	Residual	0.61764	18.16%	0.57322	20.96%
Season by Year	Time Period	0.02308	0.75%	0.01246	0.67%
	Spatial Unit	0.50367	16.37%	0.32015	17.27%
	Mode	2.0107	65.36%	1.09058	58.84%
	Residual	0.53898	17.52%	0.44273	23.89%
Month	Time Period	0.04253	1.30%	0.02891	1.40%
	Spatial Unit	0.52308	15.98%	0.34068	16.55%
	Mode	2.08782	63.77%	1.22108	59.32%
	Residual	0.62067	18.96%	0.46776	22.72%
Month by Year	Time Period	0.02863	1.05%	0.01496	1.28%
	Spatial Unit	0.40247	14.71%	0.21737	18.61%
	Mode	1.77498	64.90%	0.56038	47.97%
	Residual	0.52907	19.34%	0.37541	32.14%
Year	Time Period	1.47E-14	0.00%	0.002763	0.10%
	Spatial Unit	6.07E-01	19.65%	0.437238	16.27%
	Mode	2.04E+00	66.06%	1.729459	64.34%
	Residual	4.42E-01	14.30%	0.518587	19.29%

6.6 Active Mode Level Model

After aggregating trips by mode, a subset of the dataset that includes trips conducted by walking or biking was taken out and used for modelling. A random effects model was then estimated with the log of trip distance as the dependent variable for a set of models, and the log of trip counts by mode for another set of models. The grouping factors (random effects) considered were mode, region and different time periods (season, year, month, season by year, month by year). Only the region grouping factor was considered for spatial units due to the small sample size of trips conducted by active modes. That is, the number of trips, or total trip distance covered, by active modes would have been too thinly distributed across different municipal sectors for analysis purposes. Table 6-10 summarizes the obtained VPC results.

Table 6-10 Active Mode VPC Analysis

		Trip Distance	Trip Rates

Time Period	Cluster	Variance	VPC	Variance	VPC
Season	Time Period	0.4605	23.96%	0.4056	14.50%
	Region	0.4846	25.21%	0.5183	18.53%
	Mode	0.3465	18.03%	1.3849	49.50%
	Residual	0.6304	32.80%	0.489	17.48%
Season by Year	Time Period	0.2917	18.01%	0.2028	9.39%
	Region	0.5671	35.01%	0.5315	24.62%
	Mode	0.2513	15.51%	1.1135	51.57%
	Residual	0.5097	31.47%	0.3114	14.42%
Month	Time Period	0.3356	18.34%	0.2897	11.63%
	Region	0.56	30.61%	0.5372	21.57%
	Mode	0.323	17.65%	1.2561	50.43%
	Residual	0.611	33.40%	0.4078	16.37%
Month by Year	Time Period	0.1418	10.21%	0.1075	6.47%
	Region	0.475	34.21%	0.4352	26.19%
	Mode	0.1346	9.70%	0.8035	48.36%
	Residual	0.6369	45.88%	0.3153	18.98%
Year	Time Period	0.02391	2.87%	0.00993	0.62%
	Region	0.5986	71.87%	0.60677	38.18%
	Mode	0.11165	13.40%	0.89716	56.45%
	Residual	0.09879	11.86%	0.07549	4.75%

Interestingly, the VPCs of the variable temporal variables were significant at the 95% confidence interval (with the exception of the year variable for the trip counts model) and ranged from 1% to 25%. That is, approximately 1% to 25% of the variation in travel behavior, whether it is trip distance or number of trips, is attributed to between time period differences (e.g. season to season). This means that, in the case of active modes, the temporal nature of the data are heteroscedastic. This is in contrast to the conclusion of section 6.5, where the temporal component of the estimated models proved negligible in explaining the variation in travel behavior. Here lies the advantage of continuous surveys, as their continuous data elements can be leveraged to conduct time series analysis and identify temporal trends for various policy purposes.

In the case of total travel distance covered, anywhere from 25% to 71% of the total variance may be attributed to between-region differences. Further, modal differences still played a role in explaining the dependent variable variance (10% to 18%). On the other hand, in the case of trip rates, or count of trips by mode, between mode differences played a bigger role in explaining the variance of the dependent variable. That may be because, while the trip distances covered by walking and cycling can likely be very similar, the number of trips by each mode can vary significantly. It is also possible that such trips are under-reported in the Montreal Continuous Survey. The same set of models were estimated for the remaining dataset that included all other modes with the exception of walking and biking. The variance component in travel behavior attributed to the temporal component of the model was below 1%.

6.7 Results of GLMM Modelling Exercise

The final VPC analysis conducted in section 6 identified that up to 25% of the total variation in trip distance for active modes can be attributed to between time period differences. Nevertheless, it remains imperative to understand the factors that determine whether an individual is likely to choose an active mode or a motorized mode (car or transit) to conduct a trip. Therefore, based on the two pre-specified groups, a multilevel/mixed effects binary logit regression model was estimated. The final model obtained was:

$$\log\left(\frac{\pi_{ijt}}{1+\pi_{ijt}}\right) = \beta_0 + \beta_1 gender_{ijt} + \beta_2 occ\_status_{ijt} + \beta_3 driv\_lic_{ijt} + \beta_4 income_{ijt} + u_j + u_t$$

Where β_i are parameter estimates (β_0 is the intercept). Since the estimated model is a three level binary logit model, the subscript of π and the lower level variables is represented by three letters: *i*, *j*, *t*. That is, the subscript *i* represents the individual choice, *j* represents the region where the individual is nested and *t* represents the time period under which different individual choices are clustered. Further, the variable u_j represents the "region" random effect, while u_t represents the "season by year" random effect. Each time period has only one subscript as they are considered crossed against each other rather than nested.

All the variables selected were sequentially tested for significance using the chi-square test. Several model runs followed. Any variable that presented an insignificant t-stat, or had an odds ratio of 1 was consequently removed. Further, two random variables were introduced; namely, region and season by year. Table 6-11 presents the parameter estimates in their basic and exponential form, along with their respective t-stats.

Table 6-11 Results from GLMM

Variable	Description	Estimate	exp(Estimate)	t-stat
(Intercept)	N/A	-1.966	0.140	-7.03
gender2	Female	-0.094	0.910	-4.82
occ_status1	Full Time	-0.172	0.842	-5.15
occ_status2	Part Time	0.147	1.159	2.97
occ_status3	Student	0.201	1.223	5.61
occ_status5	Work at Home	0.395	1.484	6.87
occ_status6	Retired	0.522	1.686	9.18
driv_lic2	No License	0.959	2.610	38.52
income2	\$20,000 - \$40,000	-0.193	0.824	-6.10
income3	\$40,000 - \$60,000	-0.286	0.751	-8.55
income4	\$60,000 - \$80,000	-0.343	0.710	-9.54
income5	\$80,000 - \$100,000	-0.428	0.652	-10.10
income6	\$100,000+	-0.525	0.591	-13.78
VPC Analysis				
Level 1 variance	Residual	84.0%		
Level 2 variance	Region	15.3%		
Level 3 variance	Season by Year	0.7%		
Number of active mode users			14,012	
Number of motorized mode users			89,267	
Log Likelihood			-36,351	

The female variable was significant at the 95% confidence interval with an odds ratio of 0.91. This means that the odds of a female travelling via walking or biking on a work day are 0.91 times that of males, or a 9% multiplicative decrease in odds. This is in line with previous research on the topic (Garrard, et al., 2008) (Saelens, et al., 2003). A more substantive investigation including a breakdown by age, occupation, and marital status may be needed to draw better conclusions.

In the case of occupation status, unless the individual is a full-time worker, it seems more likely for an individual to travel using walking and/or cycling as compared to the *other* category (which we have previously assumed to be the unemployed category). For example, the odds of a student are 1.223 that of an *other* worker to travel via walking or biking on a particular day – a 22% multiplicative in odds. It is difficult to make strict conclusions about the relationship between occupation status and mode of travel without looking at the location of residence and that of work. In addition, contrasts are necessary to better understand the relationships between the different groups compared to one another.

Not having a driving license presented a 161% increase in odds of travelling via walking or cycling. This may be reasonable as many non-driving individuals may have to resort to active modes and/or transit to make their needs meet (Mahmoud, et al., 2015). Moreover, an increase in income was associated with a decrease in odds, as compared to the base of very low income. For example, if a household is making over $100,000 a year, the odds of the individual residing in such a household are 0.59 times that of a household making less than $20,000 a year to travel via walking or biking – a 41% multiplicative decrease. This is no surprise as households with higher incomes can afford alternative means of transport that may be inaccessible to the lower income population.

The variance partition coefficients of the random effects were also calculated. The model estimated that approximately 15% of the residual variance in the propensity to use active modes of travel is attributed to between-region differences, less than 1% is attributed to between season differences, and the rest is attributed to between trip choice differences. The results if the VPC analysis indicates that the choice of mode (active vs motorized) is less dependent on the season of the trip. This may be interpreted by the fact that individuals may still choose to walk or bike year round.

7 Conclusion

In this thesis, the issue of sample size determination for both cross-sectional and continuous household travel surveys was investigated. The issue of sample size, while a contentious issue in household travel survey design, has not received sufficient attention in the literature. In the light of the increase in adoption in new survey types, mainly continuous household travel surveys, it was deemed necessary to pursue a deeper understanding of the sample size requirements for demand modelling and the development of statistically adequate OD matrices.

Moreover, this thesis also investigated the state of practice of continuous household travel surveys. It is believed that such surveys present two main advantages over their cross-sectional counterparts. First, it has been proposed that the adoption of continuous surveys can result in efficiency gains as the survey process is ongoing. This can translate to a reduction in overall costs, especially since the high startup capital of cross-sectional surveys is not needed. Second, large streams of continuous data can be used to depict travel patterns and behaviour over time, whether it be months, seasons or years. It is difficult to examine the authenticity of the first claim without actually conducting a continuous survey. However, the second claim is put to the test by examining travel behavior variance attributed to different time periods.

7.1 On The Issue of Sample Size

An extensive review of existing literature revealed different global practices. Only Canadian regions have been able to maintain large sample household travel surveys while most other countries have chosen a smaller sampling rate, or adopted new approaches like continuous surveys. Toronto and Montreal are prime examples of cities implementing large cross-sectional surveys. While the move towards small sample household travel surveys is mainly driven by budget limitations, the theoretical justification was not necessarily neglected. However, although small sample sizes are theoretically acceptable, the approach often fails to provide sufficient data for long-term trend analysis and disaggregate travel demand modelling. The Canadian examples have proven that, even with the increasing cost of implementing surveys, it is possible to maintain large sample household travel surveys.

Nevertheless, it has been also proven that a large sample size survey does not necessarily equate to a representative survey. The empirical investigation revealed that even the TTS with a sample size of 159,157 households (a 5% sample) can have an error of over 15% in representing basic population cohorts and attributes. Further, this study indicated that the sample size requirements for constructing a statistically adequate OD matrix are proportional to the CV ratio of the population. The sample size also increases if the region or country intent is to capture OD pair trip counts at a more disaggregate level (e.g. by mode, time of day, trip purpose, etc.).

The thesis then shifted focus to the issue of sample size in the context of continuous surveys. It was determined that the adoption of continuous surveys can lead to a reduction in sample size requirements, as data are continuously collected over time. Further, a Bayesian methodology was put forward to update OD matrices using continuous streams of data. Updating OD matrices with continuous waves of data has been encouraged in literature, but none of the researchers have opted to propose a methodology explaining how. By updating OD matrices, it is expected that the overall sample size requirements for depicting travel behavior are likely to decrease.

7.2 On The Capacity of Continuous Surveys in Capturing Temporal Travel Behavior

This thesis provided a comprehensive review of the state and practice of continuous household travel surveys. Lessons were compiled from countries and regions around the world on the feasibility and usefulness of continuous surveys for modelling and planning. The findings of the literature review conducted in this thesis indicate that continuous data can be pooled over a certain timeframe to provide input for travel demand modelling. Apart from the structure of the survey, weighting, expansion and validation techniques were introduced. More explicitly, weighting and/or expansion factors can be calculated by taking the inverse probability computed for all households while factoring in temporal variability and non-response. The time period at which data should be pooled requires an empirical analysis using the collected continuous data. Nevertheless, past research has shown that pooling over a 3-year period may be ideal. It was also determined that a large sample size - equivalent to at least 1% of the total region population per annum - and a methodologically sound continuous survey may be sufficient for the data requirements of travel demand models.

The thesis then investigated the claim concerned with the ability of data collected from continuous household surveys in capturing the temporal variability over time. The dataset in use was that of the Montreal Continuous Survey; a 4-year continuous survey conducted from 2009 to 2012. A mixed method modelling approach was adopted, followed by a VPC analysis to identify the variance contribution of different time periods on travel behavior. The modelling exercise was conducted on the individual, household, regional, trip, and modal level.

The VPC analysis results suggested that only a very small percentage of the total variation in total trip distance travelled by individuals and/or households in a typical weekday may be attributed to the variation between time periods. On the other hand, up to 35% and 25% of the total variance in trip distance and/or trip counts conducted on the spatial and active modal level may be explained by the differences between time periods. Therefore, it can be concluded that continuous surveys are capable of capturing temporal changes in travel behavior on a more aggregate level, such as a spatial unit or modes that exhibit heteroscedastic travel patterns over time.

7.3 Thesis Limitations & Recommendations for Future Work

The study on sample size does not come without limitations. The effect of stratified sampling (or other forms of sampling for that matter) on sample size has not been accounted for. Further, although It has been established that the CV is a major determinant of sample size, limited effort has been invested in understanding the variance exhibited in different forms of travel behavior. Moreover, the relationship between the different types of bias and sample size was not expanded on. Finally, further research should also be conducted on the relationship between continuous surveys and sample size requirements.

This thesis investigated solely the issue of sample size requirements for household travel surveys without necessarily considering the issues of survey cost and sampling frame. Identifying an appropriate sampling frame is a critical factor that can inhibit the representation of large-scale household travel surveys. It is necessary to investigate whether any innovative or hybrid sample frame and/or survey mode (e.g. smart phone, GPS, etc.) can further reduce the base cost of household travel surveys. Further, while budget limitations are an unavoidable reality, it is important to investigate the direct and indirect benefits of large-scale household travel surveys, including potential future money savings from limiting the implementation of inefficient infrastructure investments. Such savings can offset and justify the high cost of large-scale household travel surveys.

As for continuous surveys, random coefficients were not introduced as part of the modelling structure. Such variables can alter the variance of the dependent variable, thus affecting the calculated VPCs. Further, to develop a more elaborate understanding of the Montreal metropolitan area trip behavior, it is imperative to also investigate the subset of the population that did not conduct any trips on the day of the survey. It is also important to implement the proposed methodology for updating OD matrices using a real-life dataset, such as the Montreal Continuous Survey.

References

Agence métropolitaine de transport, 2008. *Enquête Origine-Destination 2008 La mobilité des personnes dans la région de Montréal,* Montreal: l'enquête OD 2008.

Ampt, E. & Ortuzar, J., 2004. On best practice in continuous large-scale mobility surveys. *Transportation Reviews,* 24(3), pp. 337-363.

Ampt, E. & Stopher, P., 2006. Mixed Methods Data Collection in Travel Surveys: Challenges and Opportunities. *Presented at the 28th Australian Transport Research Forum.*

Bolbol, A., Cheng, T., Tsapakis, I. & Chow, A., 2012. Sample size calculation for studying transportation modes from GPS data. *Procedia-Social and Behavioral Sciences,* Volume 48, pp. 3040-3050.

Bonnel, P., Jean-Loup, M. & & Armoogum, J., 2007. *National Transport Surveys: What Can We Learn from International Comparisons?.* Washington, D.C., In Transportation Research Board 86th Annual Meeting.

Borgoni, R., Ewert, U. & Furnkranz-Prskawetz, A., 2002. *How Important are Household Demographic Characteristics to Explain Private Car Use Patters? A Multilevel Approach to Austrian Data,* s.l.: Max Plank Institute for Demographic Research Working Paper.

Bureau of Transport Statistics, 2013. *Household Travel Survey 2011/12,* Sydney, Australia: s.n.

Cambridge Systematics Inc., 1996. *Travel Survey Manual,* s.l.: Travel Model Improvement Program. U.S. Department of Transportation.

Cascetta, E. & Nguyen, S., 1988. A Unified Framework for Estimating or Updating Origin/Destination Matrices From Traffic Counts. *Transportation Research Part B: Methodological* , 22(6), pp. 437-455.

Castillo, E., Menéndez, J. M. & Sánchez-Cambronero, S., 2008. Predicting traffic flow using Bayesian networks. *Transportation Research Part B: Methodological*, 42(5), pp. 482-509.

Cools, M., Moons, E. & Wets, G., 2010. Assessing the quality of origin-destination matrices derived from activity travel surveys: Results from a Monte Carlo experiment. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 2183, pp. 49-59.

Dey, S. & Fricker, J., 1994. Bayesian updating of trip generation data: Combining national trip generation rates with local data. *Transportation*, Volume 21, pp. 393-403.

DiPrete, T. & Grusky, D., 1990. The Multilevel Analysis of Trends with Repeated Cross-Sectional Data. *American Sociological Association*, Volume 20, pp. 337-368.

DMG, 2013. *2011 Transportation Tomorrow Survey Version 1.0 Data Guide*, Toronto: Data Management Group.

DMG, 2016. *Data Management Group. Transportation Tomorrow Survey.*. [Online] Available at: http://dmg.utoronto.ca/transportation-tomorrow-survey/tts-introduction [Accessed 2016].

Garrard, J., Rose, G. & Lo, S., 2008. Promoting transportation cycling for women: the role of bicycle infrastructure. *Preventive medicine*, 46(1), pp. 55-59.

Garson, G., 2013. *Hierarchical Linear Modelling - Guide and Applications.* 1st ed. Thousands Oak, California: SAGE Publications Inc.

Goulias, K., 2002. Multilevel Analysis of Daily Time Use and Time Allocation to Activity Types Accounting For Complex Covariance Structures Using Correlated Random Effects. *Transportation*, Volume 29, pp. 31-48.

Goulias, K., Pendyala, R. & Bhat, C., 2013. Keynote—total design data needs for the new generation large-scale activity microsimulation models. *Transport survey methods: best practice for decision making*, Volume 21.

Greaves, S. & Stopher, P., 2000. Creating a synthetic household travel and activity survey: rationale and feasibility analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 1706, pp. 82-91.

Habib, K. & El-Assi, W., 2015. How Large is too Large? The Issue of Sample Size Requirements of Regional Household Travel Surveys, the Case of the Transportation Tomorrow Survey in the Greater Toronto and Hamilton Area. *Presented at the 95th Annual Meeting of The Transportation Research Board.*

Habib, K., Swait, J. & Salem, S., 2014. Using Repeated Cross-Sectional Travel Surveys to Enhance Forecasting Robustness: Accounting for Changing Mode Preferences. *Transportation Research Part A,* Volume 67, pp. 110-126.

Hanson, S. & Johnston, I., 2013. Gender Differences in Work Trip Length: Explanations and Implications. *Urban Geography*, 6(3), pp. 193-219.

Harvey, A. S., 2003. Time-space diaries: Merging traditions. *Transport survey quality and innovation*, pp. 151-180.

Kish, L., 1965. *Survey Sampling.* New York: John Wiley & Sons Inc.

Kollo, H. & Purvis, C., 1984. Changes in regional travel characteristics in the San Francisco Bay Area: 1960-1981. *Transportation Research Record,* Volume 987, pp. 57-66.

Kunzmann, M., 2013. *2010-2012 California Household Travel Survey Final Report Appendix,* s.l.: California Department of Transportation.

Lipps, O. & Kunert, U., 2005. Measuring and Explaining The Increase in Travel Distance: A Multilevel Analysis Using Repeated Cross-Sectional Travel Surveys. *DIW-Diskussionspapiere,* Volume 492.

Maher, M., 1983. Inferences on trip matrices from observations on link volumes: a Bayesian statistical approach. t*ransportation Research Part B: Methodological,* 17(6), pp. 435-447.

Mahmoud, M., El-Assi, W., Habib, K. & Shalaby, A., 2015. How Active Modes Compete With Motorized Modes in High-Density Areas: A Case Study of Downtown Toronto. *Canadian Transportation Research Forum.*

Meyer, M. & Miller, E., 2001. *Urban Transportation Planning.* Second ed. New York: McGraw-Hill.

Miller, E. et al., 2012. *Changing Practices in Data Collection on the Movement of People,* Quebec: Lee-Gosselin Associates Limited.

Mustel Group, R. M. & Halcrow, 2010. *TransLink's 2008 Regional Trip Diary Survey: Final Report.,* Vancouver: Translink.

National Institute of Statistics and Economic Studies, 2004. *Census Survey.* [Online] Available at: http://www.insee.fr/en/methodes/default.asp?page=definitions/enquete-de-recensement.htm
[Accessed 2015].

NCHRP, 2008. *National Cooperative Highway Research Program. Report 571: Standardized Procedures for Personal Travel Surveys,* Washington, D.C.: Transportation Research Board.

NYMTC & NJTPA, 2014. *2010/2011 Regional Household Travel Survey Final Report,* s.l.: New York Metropolitan Transportation Council & North Jersey Transportation Planning Authority.

Ohnmacht, T., Reimann, K. & & Brügger, A., 2012. *Swiss Microcensus on Mobility and Transport 2010–Introduction of the routing-tool and adjusting estimated distances in previous Swiss Microcensuses on Mobility and Transport.* Ascona, paper presented at 12th Swiss Transport Research Conference.

Ortuzar, J., Armoogum, J., Madre, J. & Potier, F., 2010. *Continuous mobility surveys: The state of practice,* s.l.: Transport Reviews.

Ortuzar, J. & Willumsen, L., 2011. *Modelling Transport.* 4th ed. s.l.:Wiley.

Peachman, J. & Battellino, H., 2007. The Joys and Tribulations of A Continuous Survey. *International Conference On Transportation Survey Quality and Innovation.*

Perrakis, K. et al., 2012. A Bayesian approach for modeling origin–destination matrices. *Transportation Research Part A,* Volume 46, pp. 200-212.

Pointer, G., Stopher, P. & Bullock, P., 2004. Monte Carlo simulation of household travel survey data for Sydney, Australia: Bayesian updating using different local sample sizes. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 1870, pp. 102-108.

Press, J., 1982. *Applied Multivariate Analysis: Using Bayesian and Frequentist Methods of Interest.* Second Edition ed. Malabar, Florida: Robert E. Krieger Publishing Company.

Rabe-Hesketh, S. & Skrondal, A., 2012. *Multilevel and Longitudinal Modelling Using Stata.* Texas: Stata Press.

Resource Systems Group, 2014. *The scope of Services,* City of Calgary: s.n.

Richardson, A., Ampt, E. & Meyburg, A., 1995. *Survey Methods for Transport Planning.* Melbourne: Eucalyptus Press.

Roorda, M., Carrasco, J. & Miller, E., 2009. An integrated model of vehicle transactions, activity scheduling and mode choice. *Transportation Research Part B: Methodological*, 43(2), pp. 217-229.

Saelens, B., Sallis, J. & Frank, L., 2003. Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures. *Annals of behavioral medicine*, 25(2), pp. 80-91.

Salem, S. & Habib, K., 2015. Use of Repeated Cross-Sectional Travel Surveys To Develop a Meta Model of Activity-Travel Generation Process Models: Accounting for Changing Preferences in Time Expenditure Choices. *Transportmetrica A: Transportation Science,* 8(11), pp. 729-749.

Scott, M., Shrout, P. & Weinberg, S., 2013. Multilevel Modelling Notation-Establishing Commonalities. In: *The SAGE Handbook of Multilevel Modelling.* London: SAGE Publications Ltd.

Searls, D. T., 1964. The utilization of a known coefficient of variation in the estimation procedure. *Journal of the American Statistical Association,* 59(308), pp. 1225-1226.

SEFTC, 2014. *2015 Southeast Florida Household Travel Survey,* s.l.: Southeast Florida Transportation Council.

Siikamaki, J. & Layton, D., 2007. Discrete choice survey experiments: A comparison using flexible methods. *Journal of Environmental Economics and Management,* 53(1), pp. 122-139.

Smith, M., 1979. Design of Small-Sample Home-Interview Travel Surveys. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 701, pp. 29-35.

StatsCan, 2011. *Statistics Canada. Census Data.,* s.l.: Canadian Census Analyzer.

Steele, F., 2008. Module 5: Introduction to Multilevel Modelling Concepts. In: *Learning Environment for Multilevel Methodology and Applications.* s.l.:University of Bristol, Centre for Multilevel Modelling.

Steele, F., 2011. Module 15: Multilevel Modelling of Repeated Measures Data. In: *Learning environment for multilevel methodology and applications (LEMMA). University of Bristol..* s.l.:University of Bristol, Centre for Multilevel Modelling.

Steele, F., 2011. Module 6: Regression Models for Binary Response Concepts. In: *Learning environment for multilevel methodology and applications.* s.l.:University of Bristol, Centre for Multilevel Modelling.

Steele, F., 2011. Module 7: Multilevel Models for Binary Responses. In: *Learning environment for multilevel methodology and applications.* s.l.:University of Bristol. Center for Multilevel Modelling.

Stopher, P., 1982. Small-sample home-interview travel surveys: Application and suggested modifications. *Transportation Research Record,* Volume 886, pp. 41-47.

Stopher, P., FitzGerald, C. & Xu, M., 2007. Assessing the Accuracy of The Sydney Household Travel Survey With GPS. *Transportation,* Volume 34, pp. 723-741.

Stopher, P. & Greaves, S., 2007. Household Travel Surveys: Where Are We Going?. *Transportation Research Part A,* Volume 41, pp. 367-381.

Stopher, P. & Jones, M., 2001. *Developing Standards of Transport Survey Quality,* South Africa: International Conference on Transport Survey Quality and Innovation: How to Recognize It and How to Achieve It..

Stopher, P., Kockelman, K., Greaves, S. & Clifford, E., 2008. Reducing Burden and Sample Sizes in Multiday Household Travel Surveys. *Transportation Research Record: Journal of the Transportation Research Board,* Issue 2064, pp. 12-18.

Stopher, P., Zhang, Y., Armoogum, J. & Madre, J., 2011. *National household travel surveys: The case for Australia.* Adelaide, South Australia, Australia, In 34th Australasian Transport Research Forum (ATRF).

The City of Calgary, 2016. *About My Travel Log.* [Online]
Available at: https://mytravellog.ca/web/pages/survey?locale=en-US

Train, K., 2009. *Discrete Choice Methods with Simulation.* Second ed. New York: Cambridge University Press.

Tremblay, P., 2014. *An overview of OD-Surveys in Quebec.* [Online]
Available at: http://uttri.utoronto.ca/files/2014/10/5-Tremblay-An-Overview-of-OD-Surveys-in-Quebec.pdf
[Accessed 2015].

United States Census Bureau, 2015. *American Community Survey.* [Online]
Available at: https://www.census.gov/programs-surveys/acs/about.html
[Accessed 2015].

Verreault, H. & Morency, C., 2011. Transcending the Typical Weekday with Large-Scale Single-Day Survey Samples. *Transportation Research Record: Journal of the Transportation Research Board,* Volume 2230, pp. 38-47.

Yang, H., Sasaki, T. & Lida, Y., 1992. Estimation of Origin-Destination Matrices From Link Traffic Counts on Congested Networks. *Transportation Research Part B: Methodological,* 26(6), pp. 417-434.

Yee, J. & Niemeier, D., 1996. *Advantages and Disadvantages: Longitudinal vs. Repeated Cross-Section Surveys,* California, USA.: Federal Highway Authority.

Zmud, J., Chlond, B., Kuhnimhof, T. & Richardson, A., 2011. *Background Research - Feasibility Study for a Continuous Household Activity Survey Program,* City of Calgary: PTV NuStats.

Zmud, J., Freedman, J., Chlond, B. & Kuhnimhof, T., 2011. *Feasibility Study for a Continuous Household Activity Survey (CHASP),* City of Calgary: s.n.

Appendix

Log Likelihood and AIC Results for Models

Table 1-A Log Likelihood and AIC Results for Region Models

	Individual Level		Household Level		Spatial Level		Trip Level		Modal Level	
	logLik	AIC	logLik	AIC	logLik	AIC	logLik	AIC	logLik	AIC
Season	-116928	233892	-56184	112389	25	-43	-132385	264806	-357	724
Season by Year	-116919	233873	-56151	112323	81	-153	-132385	264807	-1286	2583
Month	-116929	233894	-56184	112390	62	-115	-132385	264806	-998	2005
Month by Year	-116921	233877	-56157	112335	73	-139	-132384	264805	-3604	7219
Year	-116928	233892	-56155	112331	34	-59	-132415	264866	-300	610
Day of Week	N/A	N/A	N/A	N/A	-839.1	1686.2	N/A	N/A	N/A	N/A
Day of Week by Year	N/A	N/A	N/A	N/A	110.7	-213.4	N/A	N/A	N/A	N/A

Table 2-A Log Likelihood and AIC Results for Municipal Sector Models

	Household Level		Spatial Level		Trip Level		Modal Level	
	logLike	AIC	logLike	AIC	logLike	AIC	logLike	AIC
Season	-58512	117045	156	-303	-131067	262170	-4392	8795
Season by Year	-58481	116984	-377	763	-131069	262174	-13504	27018
Month	-58510	117042	-266	542	-131068	262172	-10575	21159
Month by Year	-58485	116991	-3642	7293	-131068	262171	-28822	57654
Year	-58486	116993	214	-418	-131097	262230	-4374	8757
Day of Week	N/A	N/A	-956.3	1922.7	N/A	N/A	N/A	N/A
Day of Week by Year	N/A	N/A	78	-146	N/A	N/A	N/A	N/A

Table 3-A Log Likelihood and AIC Results for Active Mode Models

	Trip Distance		Trip Rates	
	logLike	AIC	logLike	AIC
Season	-88.7	187.4	-83.2	176.5
Season by Year	-296.7	603.4	-241	491.9
Month	-244.3	498.5	-212	433.9
Month by Year	-842.7	1695.4	-624.3	1258.7
Year	-36.8	83.6	-30.5	71