Exploring the evolution of travel behavior and its relationship with the built environment: A Montreal case study

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Abstract

The built environment has been found to be associated with various travel outcomes such as car usage, mode choice, energy, emissions, etc. Consequently, there has been much effort to improve built environment characteristics to mitigate transport-related issues. This research aims at quantifying the effect of the built environment on travel behavior outcomes, specifically greenhouse gas emissions and active transportation (cycling) over time. First, we estimate the impact of changes in the built environment on emissions under different regional development plans. Second, we explore the evolution and links between utilitarian cycling and neighborhood typologies.

In the first part of our research, a regression model is developed in order to estimate census-tract level average household CO_2 emissions as a function of urban form and socio-demographic characteristics. Future CO_2 emissions are forecasted for the year 2031 under three scenarios – business-as-usual, in accordance with the region's sustainable development plan, PMAD, and population forecasts by the provincial transport agency, MTQ. We find that the forecast average household CO_2 emissions for 2031 are lower in the PMAD scenario by 9.7 and 5.8 percent in comparison to the business-as-usual and MTQ scenarios, respectively. Thus, we can expect that a reduction of CO_2 emissions can be achieved by 2031 given that the plans detailed in the PMAD are successfully implemented. However, these results also highlight the need for implementing alternative strategies in parallel in order to reduce emissions even further, such as the improvement of the motor-vehicle fuel efficiencies and electrification. Urban form strategies alone would not be sufficient to achieve government objectives on climate change in the short term.

The second part of the research aims to further understand the evolution of cycling for commute trips in different neighborhood typologies of Montreal over time (using O-D data from 1998 to 2008). We explore the connections between residential location and cycling through three different methodological approaches; (i) a binary logit model; (ii) a simultaneous equation model; and (iii) propensity score matching. We find that neighborhood effects have been increasing over the study period. Furthermore, after controlling for residential self-selection, we find that living in urban neighborhoods increases the likelihood of cycling to work and are able to quantify the degree to which preferences towards cycling have been increasing over time. Finally, we observe that commuters living close to the central business district have been increasingly commuting to work by foot, at the expense of cycling.

Résumé

L'environnement bâti s'avère être associé à plusieurs aspects concernant les déplacements, tels que le choix modal, la consommation d'énergie, les émissions de polluants, etc. En conséquence, des efforts importants ont été faits pour améliorer les caractéristiques de l'environnement bâti afin d'atténuer les problématiques reliées aux transports. Cette recherche vise à quantifier l'effet de l'environnement bâti sur les résultats du comportement de la mobilité, plus spécifiquement, sur les émissions de gaz à effet de serre et le transport actif (cyclisme). En premier lieu, on estime l'impact de l'environnement bâti sur les émissions de polluants sous différents plans de développement régional. En deuxième lieu, on explore l'évolution des liens entre le cyclisme utilitaire et la typologie des quartiers.

Dans la première partie de la recherche, un modèle de régression est développé afin d'estimer la moyenne des émissions de dioxyde de carbone par ménage au niveau des secteurs de recensement en fonction de la forme urbaine et des caractéristiques sociodémographiques. La prévision, en 2031, des émissions futures de dioxyde de carbone est effectuée en considérant trois scénarios : scénario de base, scénario décrit par le plan régional de mobilité durable, et scénario de prévision de la population du Ministères des Transports du Québec. En considérant le plan régional de mobilité durable, on estime une baisse des émissions futures de dioxyde de carbone de 9,7 % et de 5,8 % par rapport aux émissions estimés dans les scénarios de base et du Ministères des Transports du Québec, respectivement. En effet, suivant une mise en œuvre réussie du plan régional de mobilité durable, on pourra s'attendre à une réduction des émissions de gaz carbonique en 2031. Cependant, ces résultats soulignent aussi le besoin de la mise en place de stratégies alternatives en parallèle afin de réduire davantage les réductions des émissions. Ces stratégies peuvent impliquer l'amélioration du rendement et l'électrification de la flotte de véhicules motorisés. Les stratégies visant la forme urbaine seule ne pourront pas suffire pour atteindre les objectifs à court terme du gouvernement en matière de changement climatique.

La deuxième partie de la recherche vise à mieux comprendre l'évolution du cyclisme pour les déplacements pendulaires dans différents typologies de quartier de Montréal (en utilisant des données d'origine/destination de 1998 à 2000). On explore les liens entre la localisation des résidences et le cyclisme par le biais de différentes approches méthodologiques : (i) modèle logit binaire, (ii) modèle à équations simultanées, et (iii) méthode de l'appariement sur les scores de propension. Il s'avère que les effets de quartier augmentaient durant le période de l'étude. De plus, suite à la considération de l'auto-sélection résidentielle, on note que les résidents de quartiers urbains ont une plus grande tendance à utiliser le vélo pour se rendre au travail. Finalement, on observe que la résidence au centre-ville affecte de plus en plus négativement le cyclisme utilitaire au fil du temps.

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Contribution of Authors

Please note that some chapters may be presented at future conferences. These papers were written in collaboration with other authors including Amir Zahabi, Zachary Patterson, and Luis Miranda-Moreno.

The study on the evolution of cycling will be presented at the Transportation Research Board (TRB) 94th Annual Meeting in 2015. The previously mentioned authors were also mainly responsible for editing the paper.

My contribution to this research comprises of the data collection, cleaning, and analysis included in this research with the exception of the estimation of trip-level CO_2 emissions for previous Origin-Destination survey years of 1998, 2003, and 2008, which was completed by Amir Zahabi. Under the direction of my supervisors, I have prepared all sections of this document.

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Appendix A

1. Introduction

1.1. Context

During the last few decades, there has been much effort devoted to studying various facets of passenger transport. From these studies, we now have a better understanding of the different factors influencing travel behavior and the resulting benefits and externalities. For example, the links between the built environment and travel behavior have become clearer. Certain built environment characteristics have been found to promote non-motorized travel, while others strengthen the automobile-dependency of travelers. At the same time, the externalities of motorized travel, including harm to the environment, economy and health have been widely recognized. Air pollution has been determined to be one of the worst externalities, as the link between climate change and the observed increase of anthropogenic greenhouse gas (GHG) concentrations has been globally recognized. In recognition of both the influential role of the built environment on travel behavior and the externalities of motorized travel, much policy making has invested effort into creating environments that encourage sustainable passenger travel.

1.2. Objectives & Methodology

The objectives of this research are twofold: (i) forecast CO_2 emissions produced by passenger transport under different built environment scenarios; and (ii) explore the effects of neighborhood typologies on cycling as well as its evolution. Below, the motivations, objectives and methodologies for this research are outlined for each of the two sections of the document.

Due to increasing concerns of climate change and emerging sustainable technologies, CO_2 emissions forecasting has become a topic of interest in the field of transportation planning. Improved statistical modelling and traffic simulation software have allowed reliable estimates of CO_2 emissions. However, there is limited research on calculating CO_2 emissions over time for passenger transport due to the uncertainty of factors that affect motorized travel, such as energy prices, attitudes and technological innovations. Our research aims to overcome some limitations of previous research by developing a model that is not only able to explain recent CO_2 emissions trends, but also able to forecast future CO_2 emissions for passenger transport under different scenarios. The findings of this research will allow better understanding of which built environment policies would generate the greatest reductions in CO_2 emissions. There are two main steps for this analysis: (i) develop region-specific models to estimate average household CO_2 as a function of BE and SE characteristics for the Greater Montreal area; and (ii) forecast future average household CO_2 emissions for three scenarios – business as usual (BAU), and in accordance to PMAD policies and MTQ population forecasts.

Unlike motorized travel which is associated with numerous externalities, active and public transportation have been praised for their positive qualities as they are more environmentally friendly and beneficial to human health. Cycling in particular has been receiving the spotlight in recent transportation planning due to its ability to be competitive for short to medium utilitarian trips while producing minimal externalities. As a result, much policy making has shifted gears towards determining specific built environment characteristics that improve cycling modal share. In this study, we aim to explore how cycling commute modal share has changed in different neighborhood types during the study period, 1998 to 2008. In other words, we are interested in the evolution of neighborhood effects, the effects of neighborhood type on an individual's likelihood to cycle to work. Three types of methodological approaches are adopted for this research: (i) a binary logit model; (ii) a simultaneous equations model; and (iii) propensity score matching. The binary logit model allows us to estimate the effect sizes of various characteristics of the trip-maker's family, the trip-maker and his physical environment, including neighborhood typologies on cycling. Whereas, the simultaneous equations model allows us to simultaneously model the probability of two choices: (i) choice of neighborhood type of residence; and (ii) mode choice (cycle or not). As a result, this model considers household location and cycling mode as an endogenous process and joint-choice, thus accounting for residential self-selection bias. Finally, the propensity score matching model allows us to capture the average treatment effect, which is the difference in cycling levels for an individual moving from one type of neighbourhood (control) to another (treatment). This is achieved by matching "identical" individuals from one neighbourhood to another based on characteristics that indicate neighbourhood preferences, then, calculating the average difference in cycling levels between the matched individuals. This is an alternative method to account for residential self-selection.

2. Forecasting Transport-Related CO_2 Emissions: Montreal Case Study

2.1. Introduction

The link between climate change and the observed increase of anthropogenic greenhouse gas (GHG) concentrations has been globally recognized in both scientific and policy communities (Hensher, 2008). In the context of Canada, research and policy making have been dedicated to reducing GHGs in the transportation sector, which accounts for 24 percent of total GHG emissions (Environment Canada 2012). Households in the province of Quebec produced the second highest total private vehicle emissions in Canada at 12,274 kt of CO_2 eq in 2007, which is approximately 21 percent of total provincial GHG emissions (Terefe 2010). Through a combination of policies and marketing strategies, the Quebec government is determined to achieve a 20 percent reduction of GHGs by 2020 with respect to 1990 levels (Gouvernement du Québec, 2012).

The primary GHG emitted through human activities is carbon dioxide (CO_2), which accounts for 78.2 percent of all GHG emissions in Canada (Environment Canada 2012). The combustion of fossil fuels such as gasoline and diesel to transport people and goods, such as private vehicle use is the second largest source of CO_2 emissions. Moreover, well-to-wheel life-cycle assessments demonstrate that transport-related CO_2 is not only emitted during the combustion of fossil fuel, but also from the extracting, refining and transporting processes of oil (Moore, 2011). Fortunately, extensive research has shed light on ways of reducing transport-related CO_2 emissions through changes of certain built environment (BE) indicators.

The scope of this study is the Greater metropolitan region of Montreal in the province of Quebec, which is the second most populous metropolitan area of Canada consisting of 3.82 million people and 1.69 million private households in 2011. In 2012, the regional planning, coordinating and financing body of Montreal, the Communauté Métropolitaine de Montréal (CMM), adopted the Plan Métropolitain d'Aménagement et de Développement (PMAD) which has a set of objectives that promote a vision of sustainable development for 2031 (CMM 2011). The PMAD focuses on the integrated planning of land use and transportation as well as the efficient allocation of additional population. These objectives parallel the general findings of extensive literature on the potential to moderate and modify travel behavior by changing the "D" variables of the built environment. The original "three Ds", coined by Cervero and Kockelman (1997) are density, diversity and design. These have been followed by an additional two "Ds", namely distance to transit and destination accessibility. In this paper, we aim to quantify the effectiveness of the PMAD's objectives of improving the "D" variables to reduce household CO_2 emissions. In order to achieve this, our study is developed in two steps: (i) to estimate a model of average household transport-related CO_2 emissions as a function of built environment (BE) and socio-demographic (SD) variables at the census tract level; and (ii) to use this model to forecast future average household CO_2 emissions for three scenarios – business-as-usual (BAU), and in accordance with PMAD policies and MTQ forecasts.

Forecasting CO_2 emissions for passenger transportation has become possible, and a topic of interest, due to increasing concerns over climate change, improved statistical modelling capabilities and emerging sustainable technologies (Rentziou et al., 2011). Moreover, accurate forecasting of travel behavior and its consequences is crucial for effective land and transport policy making. However, there is limited research on calculating transport-related CO_2 emissions, and what does exist generally involves quite coarse estimates at quite aggregate levels (Cameron et al. 2003). Furthermore, there is little research specifically on forecasting metropolitan-level CO_2 emissions for passenger transport mostly due to the uncertainty of factors that affect travel behavior (attitudes, energy prices, SD, BE) and carbon footprint per unit of travel (technological innovations) (Andrews 2008; Norman et al. 2006). Our research strives to fill part of this gap by developing a model that is not only able to explain the observed trends in CO_2 emissions, but also able to forecast future CO_2 emissions for passenger transport under different scenarios.

In order to develop a census tract-level average transport-related CO_2 emissions model, five sets of data were used. First, the Montreal Origin-Destination surveys of 1998, 2003 and 2008 were used to calculate the dependent variable, average household transport-related CO_2 emissions. Second, census-tract level census data were used as the primary source of SE variables. Third, data pertaining to transit service, which includes location of stops and average AM peak headways, were used as an independent variable representing accessibility to transit. Fourth, travel time data from the provincial ministry of transportation (Transports Québec) was used to calculate accessibility measures. Finally, calculations for some BE indicators (intersection density, job accessibility, etc.) were performed using category-specific datasets provided by various sources. The resulting log-linear regression (OLS) model was used to forecast CO_2 emissions for 2031 under each of the three scenarios.

The paper begins with a literature review and is followed by a brief description of the study region, a description of the data used, and the methodology adopted for the research. After this, the results of the estimated models and the CO_2 forecasts for 2031 are presented. The paper finishes with some concluding remarks, as well as some avenues for future research.

2.2. Literature Review

In recent years, a vast literature in the field of urban and transportation planning has been dedicated to exploring the relationship between BE and SE indicators and urban travel patterns and behavior. In this research, the key transportation outcome variables include trip frequency, trip length, and mode choice along with consequent vehicle miles travelled (VMT) (e.g. Ewing and Cervero 2010). A general review of studies of the effects of BE and SE on travel behavior show that trip frequencies are primarily a function of socio-demographic characteristics of travelers and secondarily a function of the built environment, while the opposite is true for trip lengths. Of all travel variables, mode choice is the most affected by local land use patterns, which are characterized by accessibility, density, and land-use mix. The US Environmental Protection Agency (EPA) has developed a guidance document targeted for stakeholders to improve air quality by reducing VMT through improvements in urban form (UF) (EPA 2001). Currently, the EPA promotes the implementation of proactive land use strategies such as transit-oriented development (TOD), infill development, mixed-use development and jobs/housing balance.

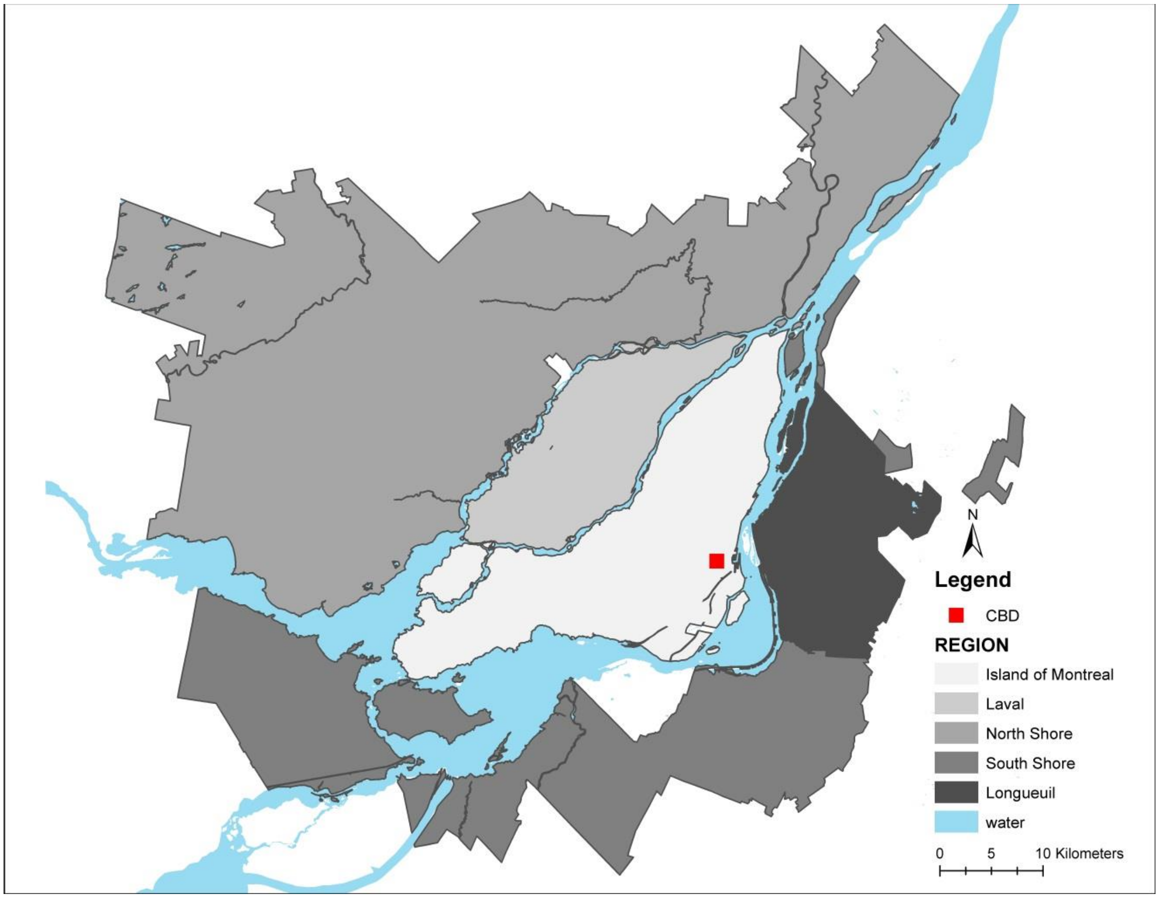
Meanwhile, other research focuses specifically on how to quantify the effects of BE on travel outcome variables. In his paper, Brownstone (2008) mentions that although there are potentially many aspects of the BE that could affect household travel behavior, research has concentrated on those aspects that are easy to measure. Also, due to the fact that most measures of the BE are highly correlated, he insists that only a few key BE characteristics may be required to capture the effects. In other literature (Bento et al. 2005), it has been found that the impact of any single BE factor may be too small to support any policy relevance. However, there is a general consensus that a cumulative impact of changing many factors may be sufficient to explain the observed changes in travel behavior. In a paper examining how the 3 Ds of BE (density, diversity and design) affect travel demand, the authors found that improvements of the 3 Ds generally reduce trip rates and encourage non-auto travel in statistically significant ways (Cervero and Kockelman 1997). In their study region, the San Francisco Bay Area, the elasticities between different indicators of travel demand and BE fell in the range of 0.063 to 0.592, in absolute terms. Recently, a literature review by the Transportation Research Board reported that a 10% increase of residential density, land use mix and accessibility cause decreases in trip length by 1 to 2.4, 0.5 and 2 percent, respectively (TRB, 2009).

The relationships between BE and travel behavior have typically been studied at the metropolitan level (Hankey and Marshall 2009). Within most metropolitan regions, there are large differences in both travel behavior and BE characteristics along the urban-suburban gradient. Twentieth century human settlement can be characterized as the outcome of two trends: (i) an increasing share of the population and economic activities into metropolitan areas; and (ii) a dispersion of population and economic activities achieved by an outward expansion of metropolitan boundaries (Anderson, Kanaroglou and Miller, 1996). The latter trend, which is commonly referred to as urban sprawl has been characterized as low-density suburban development with poor BE (Burchell et al., 2002). The low-density pattern of urban sprawl has two important effects on travel: longer trip distances and greater reliance on the car (Handy et al, 2005). Handy et al (2005) conclude that changes in BE and changes in driving demonstrate significant associations even when socio-demographics, attitudes and preferences are accounted for. The authors explain that although the analysis may not be definitive, the results are in support of land-use policies that are designed to counter sprawl including TODs.

2.3. Study Region

The study area is the Communauté Métropolitaine de Montréal (Greater Montreal) in the province of Quebec, Canada, which had a total area of 4,360 km^2 and a population of 3.7 million inhabitants in 2011. The CMM is divided into 5 geographic sectors: Montreal, Laval, Longueuil, South and North Shores (Figure 2-1). Currently, the region is dominated by the Island of Montreal as it contains 47% and 71% of the region's population and jobs, respectively (AMT, 2010). The spatial distribution of residential location and employment opportunities in the CMM serve as significant factors in determining mode choice and travel behavior, ultimately affecting transport-related CO_2 emissions produced by private households (Sider et al, 2013). Furthermore, between 2011 and 2031, the CMM is projected to welcome additional population and employment opportunities of 530,000 people or 320,000 households and 150,000 jobs, respectively (CMM, 2011). According to Plan Métropolitain d'Aménagement et de Développement (PMAD) projections of household distribution, the peripheral regions including Laval, South and North Shores are expected to experience the highest growth rates at 3 to 4 percent annually, which is more than twice as much as those of more central regions including the Island of Montreal and Longueuil. Furthermore, the CMM has a relatively extensive public transit network that extends radially from the central business district (CBD). Public transportation is offered in many forms: metro, commuter rail, express bus and regular bus. Montreal's transit network is not only one of the densest, but is one of the longest systems in North America with 1.3 kilometers per square kilometer (EIU 2011). In the upcoming years, CMM's transit network is expected to be improved with metro extensions, bus rapid transit (BRT) and light-rail (LRT) additions (AMT, 2011).

Figure 2-1 Regional Breakdown of Greater metropolitan region of Montreal (Statistics Canada, 2011)



2.4. Data

For this study, two primary datasets were used; average household CO_2 emissions at the census-tract level and explanatory BE and SE variables for the study period and future scenarios. In order to calculate average household CO_2 emissions, trip-level Origin-Destination household survey data, along with link-level speeds and motor-vehicle fleet characteristics were used. The O-D survey, which takes place every 5 years, provides urban travel information for an average weekday of residents of the greater metropolitan Montreal region (AMT, 2008). For this analysis, surveys for years 1998, 2003 and 2008 were used. The participants of the O-D survey provide details for every trip made during the previous day for every member of the household over the age of 4. For each trip, the following information is provided: origin and destination x-y coordinates, mode(s) of transportation, purpose of trip, transit lines used, time of departure, car occupancy, etc. Due to the fact that the O-D survey does not include information on the make, model or year of the vehicles owned by each household, FSA-level (first 3 digits of postal code) average motor-vehicle fleet inventory information from the provincial automobile insurance society (SAAQ) served as a substitute. From this information, vehicle fuel consumption rates (FCR) were calculated.

The BE and SE explanatory variables that were included in the model were those that were measurable, available and identified to be influential factors of travel behavior in literature (Ewing and Cervero 2010; Zahabi et al. 2012). First, census tract profiles of census data provided by Statistics Canada served as the primary source of SE measures. The Canadian census takes place every 5 years, thus, for this analysis, census years 1996, 2001 and 2006 were used. From the census, the following information was derived: number of households, number of full-time workers, number of part-time workers, number of persons under 15 years of age, number of persons between 25 and 64 years of age, number of persons over 65 years of age, average household income and modal split for commute to work. One of the critical explanatory variables is the location of jobs by sector across the region. This was available for the censuses of 1996, 2001 and 2006 as a special order from a consortium of Quebec provincial agencies known as the Consortium de données sur le lieu de Travail.

Public transit accessibility, which serves as one of the indicators of BE was calculated using transit stop and line data obtained from a variety of sources. The network for Montreal was built up as a hybrid network, composed of a base originally geocoded in TransCAD by Dr. Murtaza Haider of Ryerson University in 2003, upon which were added additional lines to cover the extent of the CMA. The development of this base network was supported by a grant from the National Sciences and Engineering Research Council (NSERC) as well as infrastructure provided by the Canada Foundation for Innovation (CFI). Off-island transit lines were subsequently added by hand in the summer of 2011. For 2031 the Plan Métropolitain d'Aménagement et de Développement (PMAD) scenario, BE and SE indicators are based on the objectives of the plan. The PMAD provides figures of population growth, indexes, and maps that provide insight to where transit lines will extend to.

Mobility data – travel times between census-tracts in the region were calculated based on networks provided by Transports Québec. These networks had congested travel times by link for the morning peak period. These networks were used to calculate shortest path travel times between aggregated (see below for details of aggregation) census tracts in TransCAD. These travel times, in combination with the employment data from the Consortium allowed for the calculation of employment and population cumulative opportunities (Hansen, 1959) accessibility indicators.

2.5. Methodology

The methodology proposed in this research extends from previous research (Zahabi et al. 2012) applying disaggregate analysis of the determinants of urban transport-related CO_2 emissions. The inventories of emissions at the trip-level were obtained from this work. For the current research, three main steps were implemented:

I. *Calculation of average household CO_2 at census-tract level:* This involves aggregation of previously calculated trip-level CO_2 for 1998, 2003 and 2008 O-D survey years.

II. *Define BE and SE indicators for the past and future:* This includes measures that account for density, diversity, destination accessibility, distance to transit and socio-demographic characteristics for 1998, 2003 and 2008. Depending on the scenario, values of SE and BE values are assigned for 2031.

III. *Quantifying the effect of BE and SE indicators:* This involves developing OLS (ordinary least squares) models that estimate average CO_2 emissions by census tract.

IV. *Forecasting CO_2 for different scenarios in 2031:* here, the model developed in step III is used to predict future average household CO_2 at the census tract level under three scenarios.

Due to socio-demographic and land use changes in the greater metropolitan area of Montreal, the areas and shapes of the census tracts evolved over the study period (1996 to 2006). In order to have a dataset that was comparable over the years, a new shapefile based on the base year (1996) census tracts was created in ArcMap 10.1. Furthermore, all census tract data was aggregated to correspond to the new comparable census tracts. As well, only households that fell in the comparable census tracts were used to calculate the CO_2 emissions.

2.5.1. Calculation of Average Household CO2 Emissions at the Census Tract Level

In previous research (Zahabi et al. 2012), trip-level CO_2 was estimated using completely disaggregate trip data and taking into account two modes: private motor vehicles and public transit. According to this approach, it was assumed that all trip-makers use a unique, or combination of modes (active transportation, private motor vehicles and public transit) to travel from the reported x-y coordinates of the origin to that of the destination (AMT, 2010). For all trips recorded in the three O-D survey years, trip level CO_2 was calculated using a procedure based on Barla et al. (2009, 2011) and Zahabi et al. (2012), where emissions for a given trip departing at a particular hour are estimated as follows.

<u>*Private motor vehicle trips:*</u>

$$CO_{2\,Aj} = \sum_{i=1}^{N} \frac{FC_{Aj} \times EF_A \times [\, D_{Aij} \times SP_{ij} \,]}{R_{Aj}} \qquad \text{(Eq.2-1)}$$

Where:

$CO_{2\,Aj}$ = $\mathrm{CO_2}$ for automobile portion of trip j (kg of $\mathrm{CO_2}$)

FC_{Aj} = average fuel consumption rate (FCR) in litres of gasoline/100km for the vehicle used in trip *j*

D_{ij} = travel distance by segment (link in network) I in 100km. For selecting trip paths, user equilibrium conditions (congested link travel times) are established using a traffic assignment platform implemented in the modelling software (EMME/3) developed and calibrated by the Quebec Transportation Ministry

EF_A = emission factor for gasoline (2.289 kg of CO_2 / litre of gasoline)

R_{Aj} = number of passengers in trip *j* including the driver

For public transit trips:

$$CO_{2\,Bj} \quad = \sum_{j=1}^{N} \frac{FC(S)_{Bj} \times D_{Bj} \times EF_B}{R_{Bj}} \qquad \text{(Eq. 2-2)}$$

Where:

$CO_{2\,Bj} \quad = CO_2$ for bus portion of transit trip j

$FC(S)_{Bj}$ = average fuel consumption rate (FCR) as a function of operating speeds (S) in litres diesel/100km. Fuel consumption rates for the typical fuel bus technology operating in real conditions were obtained from a recent field study conducted by the local transit agency, Société de transport de Montréal (STM). The fuel consumption curve according to this study is given by FC(S) = 257.8* (Bus Speed)$^{-0.48}$

D_{Bj} = distance travelled by bus for transit trip j (km) for each trip involving transit (bus, metro and commuter trains) in the Montreal region, distances were obtained from the public transit assignment software, MADIGAS . Trips were simulated in collaboration with the Agence transport métropolitain (AMT).

EF_B = emission factor for diesel (2.663 kg of CO_2/ litre of diesel)

R_{Bj} = average bus route ridership

For every trip of the O-D survey, the sum of CO_2 produced by each mode of transportation used in the trip is calculated. Then, household-level CO_2 is calculated by taking the sum of all trips made by all household members during the survey period. Households were then geocoded to the temporally constant census tract zones. Finally, the average household CO_2

at census-tract level is calculated by aggregating expanded CO_2 emissions by household and dividing by the expanded population of households within each census tract.

Average household CO_2 emissions at census tract level:

$$CO_{2\,i} = \frac{\sum_{j=1}^{N}[\, mfexp_{ij} \times CO_{2\,ij}\,]}{\sum_{j=1}^{N} mfexp_{ij}} \qquad \text{(Eq. 2-3)}$$

Where:

$CO_{2\,i}$ = average household CO_2 at census tract *i*

$mfexp_{ij}$ = expansion factor of the household *j* in census tract *i*

$CO_{2\,ij}$ = total daily household CO_2 for household *j* in census tract *i*

Due to the fact that the average household CO_2 at census-tract level is not normally distributed, the natural log of the value is used to achieve a lognormal distribution of the dependent variable in the OLS model.

2.5.2. Definition of BE and SE indicators for the study period (1998, 2003, 2008, 2031)

As mentioned in the introduction, one of the main purpose of this research is to quantify the effects of BE and SE indicators on average household transport-related CO_2 emissions. In order to achieve this, a set of explanatory variables needed to be matched to the calculated CO_2 emissions. The values for the SE indicators were derived from 1996, 2001 and 2006 census data provided by Statistics Canada. Transit accessibility was calculated based on the transit service dataset described in the previous section. Since the OD survey is conducted two years after the census, census data from the preceding census was matched to the CO_2 emissions data. That is, 2006 census data was associated with 2008 emissions data. Depending on the scenario of interest, BE and SE values for 2031 were either estimated in accordance to the 10 year trend (1998 to 2008) or derived from the long range development plan, the PMAD. If the development policies or projections did not specify forecasts for particular variables, the same values (those as developed for the reference scenario) were used. The following section demonstrates the calculations for BE and SE variables that were found to be statistically significant in the regional OLS models.

Built Environment Indicators:

- Household density (number of households/km^2)
- Intersection density (number of intersections/km^2)
- Travel time to central business district (minutes)
- Jobs within 30 minute travel time
- Entropy index
- Public transit accessibility
- Public transit modal split

Public transit accessibility: This was calculated by first finding the nearest bus, metro and rail line stops to the centroid of each census tract. Then, the contribution of each line's closest stop was summed (Zahabi et al. 2012). As a result, a transit stop that is closer from the centroid of the census tract of interest or has a smaller headway would increase the transit accessibility for that census tract. For the PMAD scenario, a combination of PMAD documentation and service extension plans from STM and AMT were used to determine the locations of new additional stops. However, as the plans are still yet to be specified, it had to be assumed that the average AM peak headways of new stops will be the same as those of neighboring stops of the same line according to 2008 data.

$$PTaccess_j = \sum_{i=1}^{n} \left(\frac{1}{d_{ij} \times h_i} \right) \qquad \text{(Eq. 2-4)}$$

Where:

$PTaccess_j$ = public transit accessibility at census tract *j*

d_{ij} = distance (km) from the centroid of census tract *j* to nearest stop of the bus/metro/rail line *i* (minimum value of 0.1 km)

h_i = average headway (hours) of line *i* during AM peak (maximum value of 1 hour)

Accessibility to Jobs: This was calculated by using two sets of data: travel time matrix calculated as described in the data section, and number of jobs by census tract. Cumulative opportunity accessibility measures were calculated for travel time of 30 minutes.

Land Use Mix: For this, a land use shapefile provided by Desktop Mapping Technologies Inc. (DMTI) was used to calculate the entropy index. Out of the seven land use categories defined in the data, only five categories were considered for the calculation, which are residential, commercial, institutional and governmental, resource and industrial, and park and recreation. The categories that were not included in the calculation are water and open area (Zahabi et al. 2012). The following equation was used.

$$E_j = \sum_{i=1}^{n} \frac{[\left(\frac{A_{ij}}{D_j}\right) \ln(\frac{A_{ij}}{D_j})]}{\ln(n)} \qquad \text{(Eq. 2-5)}$$

Where:

E_j = entropy index for census tract j

A_{ij} = area of land use i in census tract j

D_j = area of census tract j excluding water and open area

n = number of land use categories (in this study, n=5)

Socio-demographic Indicators: In order to take into account the changes to census tract divisions over the years, a correspondence table was made. All of the socio-demographic data that was derived from census tract data was associated with the census tract IDs that are consistent over the study period. The following list briefly describes the variables that were used in the model.

- Full-time workers per household
- Part-time workers per household
- Number of persons under 15 years of age per household
- Number of persons between 25 and 64 years of age per household
- Number of persons 65 years of age and older per household
- Average household income (before-tax)

The main difference between the three scenarios is the distribution of households in the region. The PMAD assumes 40% of new households (between 2011 and 2031) will locate in transit-oriented development (TOD) areas (CMM 2011). These are primarily areas around metro and commuter rail stations. In the PMAD documentation, a map of existing and projected TOD zones along with the minimum household density is provided. The projected TOD areas correspond to projected expansion of transit service lines for metro, rail and express buses. In addition, the PMAD specifies by region, the proportion of total households to be located in TOD areas in 2031 as shown in Table 2-1. The greater metropolitan area of Montreal is divided into five geographic sectors; Montreal, Laval, Longueuil, North and South Shores. Therefore, for the PMAD scenario, new households were distributed to high-density TOD areas first, then, the remaining households were distributed equally in the non-TOD areas. Given the PMAD's distribution of new households, new values were generated for household density and household to job ratio. However, as the PMAD lacks information on projected employment status of residents, these variables could not be derived from PMAD.

Table 2-1 Distribution of households by region in 2031

	2011	Scenario 1: BAU	Scenario 2: PMAD		Scenario 3: MTQ
Geographic Sector	No. of Households	No. of Households	No. of Households	% in TOD	No. of Households
Island of Montreal	867,600	981,100	900,538	63%	937,159
Laval	158,640	190,469	200,533	17%	200,618
Longueuil	170,220	298,149	285,813	14%	306,454
North Shore	212,180	200,874	193,271	12%	139,043
South Shore	182,220	196,424	197,027	15%	202,575
Total	159,860	1,867,016	1,777,182	40%	1,785,849

2.5.3. Estimating the effects of BE and SE Indicators (1998, 2003, 2008)

As previously mentioned, the greater metropolitan area of Montreal is divided into 5 regions. For this research, we wanted to capture the effect of changes in BE and SE variables through time on transport-related CO_2 emissions. Moreover, the year of observations was included as a continuous independent variable in order to capture trends in the change in CO_2 emissions over time. In order to achieve this, a separate multiple linear ordinary least squares (OLS) regression approach was adopted for each region, in which a set of BE and SE indicators are entered in the model to test for statistical significance. To meet the assumption of normality of the continuous dependent variable of linear regression models, we took the natural logarithm of the average household CO_2 emissions. The models are formulated as followed:

$$\ln(CO_{2\,i}) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_n X_{ni} + \varepsilon_i \qquad \text{(Eq. 2-6)}$$

Where:

$\ln(CO_{2\,i})$ = the natural logarithm of average household transport-related CO_2 emissions at census-tract level

β_0 = constant

β_1= model estimated coefficient for independent variable 1

X_{ni} = value of independent variable n in census tract *i*

ε_i = random independent error

2.5.4. Forecasting CO_2 for different scenarios in 2031

The final step is to use the coefficients that were derived from the log-linear OLS models to predict CO_2 emissions given the three scenarios. It is important to note that because the natural logarithm of CO_2 emissions were used as the dependent variable, predicted CO_2 emissions needed to be transformed back to the original arithmetic units. However, power and exponential models can generate biased predictions when derived by least-squares, linear regression of log-transformed variables. As a result, a series of steps were taken to remove prediction bias thus, enhancing the accuracy of subsequent predictions according to the method described by Newman (1992).

2.6. Results

The organization of this section corresponds to the order in which the methodology was undertaken. First, the inventory results of average household CO_2 emissions at the census-tract level are displayed. Then, a table summarizing SE and BE variables for all study periods follows. Third, log-linear regression models are presented. Lastly, a summary of forecasted CO_2 emissions for the three different scenarios is presented.

2.6.1. Average Household CO_2 Emissions Inventory

During the study period, both the average and total transport-related household CO_2 emissions were highest in the earliest period, 1998. From the beginning to the end of the study period, average household CO_2 emissions have decreased from 11.40 (1998) to 9.06 (2008) kg/day (Table 2-2). This translates to an average annual CO_2 emissions reduction rate of 2.1 percent.

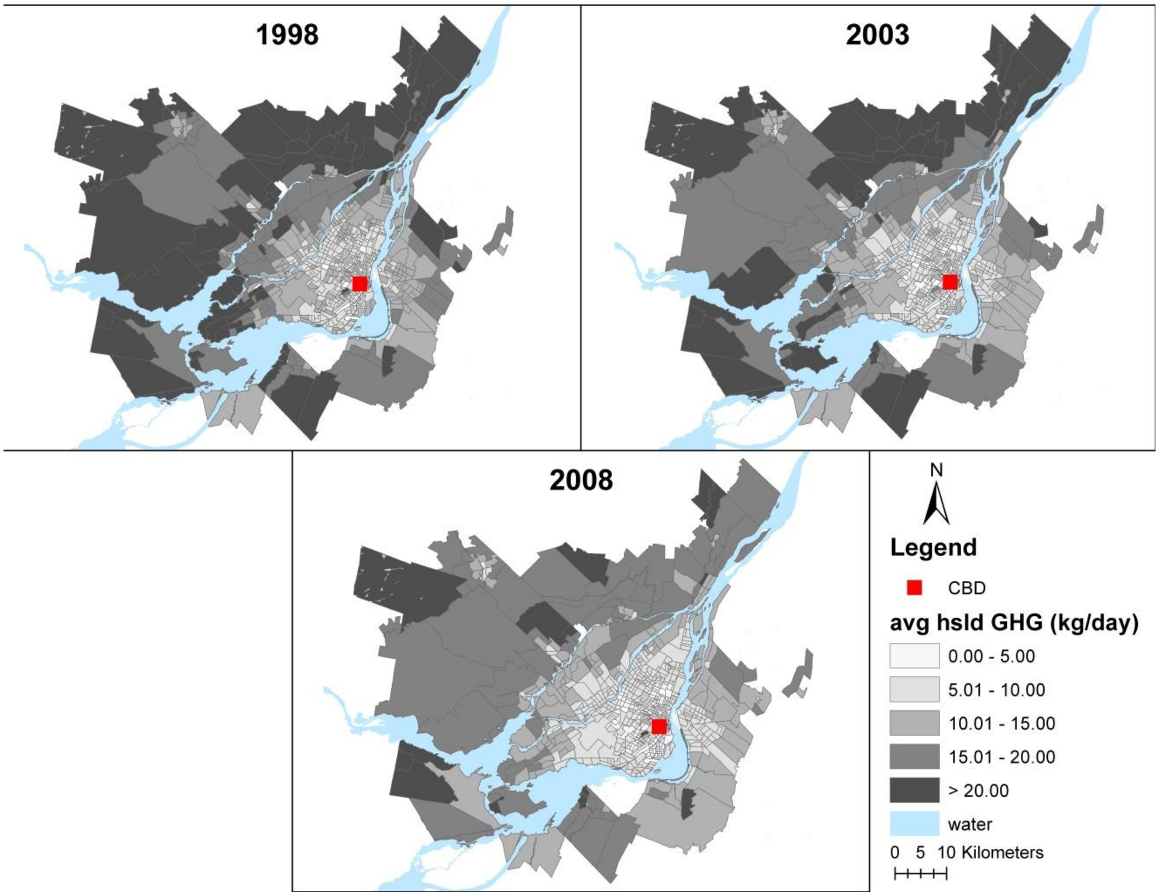
Meanwhile, during the same period, total CO_2 emissions in the region decreased from 14.68 to 13.14 kt/day, despite the addition of 161,510 new households (12.5 percent growth). This decrease is explained by several factors including increased use of active and public transportation as well as the introduction of increasingly fuel-efficient vehicles. The Tables A-11 to A-15 in Appendix A present the average and total CO_2 emissions by region. From the average household CO_2 emissions by year, we observe a decreasing trend for all regions from 1998 to 2008. The Island of Montreal experienced the greatest reductions, with annual reduction of 3 percent. Longueuil experienced the second highest reduction rate at -2.5 percent annual change in CO_2 emissions, which is followed by Laval with 2.2 percent annual reduction rate. The South Shore experienced the lowest average CO_2 emissions reduction rate with 0.7 percent, followed by the North Shore with 1.6 percent.

Table 2-2 Summary of household CO2 emissions during the study period (1998 to 2008)

Variable	1998	2003	2008
Average household CO_2 (car + transit) (kg/day)	11.40	10.00	9.06
Total number of households (millions)	1.29	1.36	1.45
Total CO_2 in CMM (kt/day)	14.68	13.61	13.14

Below, in Figure 2-2, the spatial distribution of average household CO_2 emissions at the census-tract level is presented. All households that fall within the borders of a census-tract are considered as a resident of that census tract and are included in the calculation. The maps demonstrate that with increasing distance to central business district (CBD), average transport-related household CO_2 emissions increase. This illustrates the heavy car dependence of suburban households, a phenomenon that widely prevails in North American metropolitan regions. Moreover, the maps show the trend of decreasing average household CO_2 emissions over time.

Figure 2-2 Average CO2 emissions at CT-level during study period (Statistics Canada, 2011)



2.6.2. SE and BE Indicators

Tables A-1 to A-5 in Appendix A demonstrate summaries of the average household emissions, SE and BE indicators by region. These tables convey a few general trends. First, we find that with increasing travel time to CBD, average household CO_2 emissions increase, while public transit accessibility and public transit modal share decrease. Second, household densities and job accessibilities decrease with increasing distance to CBD. Third, it is interesting to find that on the Island of Montreal (region 1), there are significantly fewer full-time workers and persons less than 15 years of age per household proportionally than any other regions. Furthermore, there is a difference between the age composition of urban dwellers and suburban dwellers. For example, households in CBD are more commonly composed of young professionals (single or couples), whereas middle-aged professionals with children are more highly represented in the suburbs.

2.6.3. OLS Model Estimations

For this study, a log-linear (OLS) regression was used to estimate the effect sizes of each SE and BE variable. The dependent variable for this model is the natural logarithm of the average household CO_2 emissions at census-tract level. Presented in Tables A-6 to A-10 in Appendix A are summaries of region-specific models that were used in the next step to forecast CO_2 emissions for the three scenarios for 2031.

We expect to see a negative coefficient for 'year' variable as we have observed decreases of average household CO_2 emissions during the study period (1998 to 2008). In terms of SE variables, we expect the following observations. First, we expect a positive coefficient for both number of full-time and part-time workers per household, where full-time has a greater value. This is due to the fact that employed individuals commute to work, which may not be in close proximity to their residence. Due to the unbalance of jobs to household ratios throughout the region, we know that a significant proportion of individuals commute from their residential locations to the central business district areas during peak hours. Second, we expect to observe positive coefficients for both the number of persons under 15 years of age and between 25 and 64 in household. Increases in the number of children and adults per household have been to be positively associated to motorized travel. For BE variables, we expect negative coefficients for all density and accessibility measures as well as land-use mix. Our expectations are derived from the general findings in literature that improved built environment is positively associated with more sustainable mode of transport as well as shorter trip distances (Ewing and Cervero 2010). Finally, we expect to observe a positive coefficient for travel time to CBD due to the fact that suburban neighborhoods generally have low accessibilities to jobs and destinations (Ewing and Cervero 2010).

From these results, we can make several observations. First, we see that households with more employed persons (full-time and part-time) produce more CO_2 emissions on average in comparison to those with unemployed members. This can be explained by the fact that the majority of workers commute to workplaces, which may not necessarily be in close proximity to their homes. Second, we observe greater CO_2 emissions with increasing household income, as wealthier households are likely to have higher car ownership and produce more vehicle-miles travelled (VMT). However, in recent years, we have seen much higher hybrid-electric vehicle penetration rates as well as higher fleet replacement rates in the high-income category (Chan et al. 2013). Therefore, in the future, the relationship between income and CO_2 emissions may be subject to change. In terms of BE indicators, we see that density and accessibility variables are negatively associated with household travel CO_2 emissions. Also, from the positive relationship between distance to CBD and CO_2 emissions, we observe that suburban neighborhoods produce greater CO_2 emissions. This is explained by the fact that in suburban neighborhoods, public transit accessibility, intersection design and activity densities are poor, discouraging alternative modes than driving. Furthermore, we find that land-use mix is negatively related to household CO_2 emissions. From this, we can assume that greater land-use diversity translates to a greater diversity of travel destinations in neighborhoods nearby.

Moreover, household density has been increasing (albeit from much lower levels) at a higher pace in outskirts compared to central neighborhoods of Montreal across all three scenarios.

Moreover, the PMAD specifies that due to the planned extensions of transit lines, TOD areas in the suburban neighborhoods are expected to be more abundant by 2031. Therefore, in the PMAD scenario, we expect the high suburban growth rates of density to have a decreasing effect on average household CO_2 emissions in the suburban neighborhoods, whereas the central neighborhoods will remain relatively unchanged.

It is important to note that the OLS model for South Shore includes significantly fewer explanatory variables, resulting in a low adjusted R^2 of 0.3285. During the model calibration process, we realized that many explanatory variables were not significant.

2.6.4. Forecasted CO_2 Emissions for 2031

The information that was specified in the PMAD document includes location of future transit lines, targets for active and public transportation modal share during AM commutes, and distribution of households. For the PMAD scenario (scenario 1), all SE and BE variables, excluding land-use mix, intersection density and average household income were assigned new values according to the objectives of PMAD. For the BAU scenario, the projections of values for all SE and BE variables were assigned. Finally, for the MTQ scenario, all SE and BE values were identical to BAU scenario except for household density (which used MTQ forecasts) and its related variables. As the PMAD scenario contains the most positive change in BE, we expect to observe lower CO_2 emissions in comparison to the other two scenarios. The CO_2 estimates and forecasts for each of the regions are presented in Tables A-11 to A-15 in Appendix A.

From these tables, we observe several general trends about CO_2 estimates and forecasts. First, the PMAD scenario produces the lowest average household CO_2 emissions in all regions with the exception of the Island of Montreal. The average household CO_2 emissions are forecasted to be 2.41, 2.41, and 2.36 kg/day for BAU, PMAD and MTQ scenarios respectively. Unlike other regions, the Island of Montreal has no significant improvements in built environment in the PMAD scenario compared to BAU scenario. Also, when allocating population for the PMAD scenario, we noticed that the minimum projected population densities were already achieved in 2008. Therefore, the majority of the additional population between 2008 and 2031 were allocated in less dense areas for the PMAD scenario. As a result, we observed that the Island of Montreal is forecasted to experience the same average household emissions for both BAU and PMAD scenarios. Longueuil is expected to experience the most reductions in average household emissions through the implementations of PMAD. In the PMAD scenario, the forecasted average household emissions for Longueuil is 2.7 kg/day, which is 29 percent less than that of the BAU scenario. The regions of Laval, North and South Shores are expected to experience 9.5, 10.0, and 8.7 percent savings in average household emissions in the PMAD scenario.

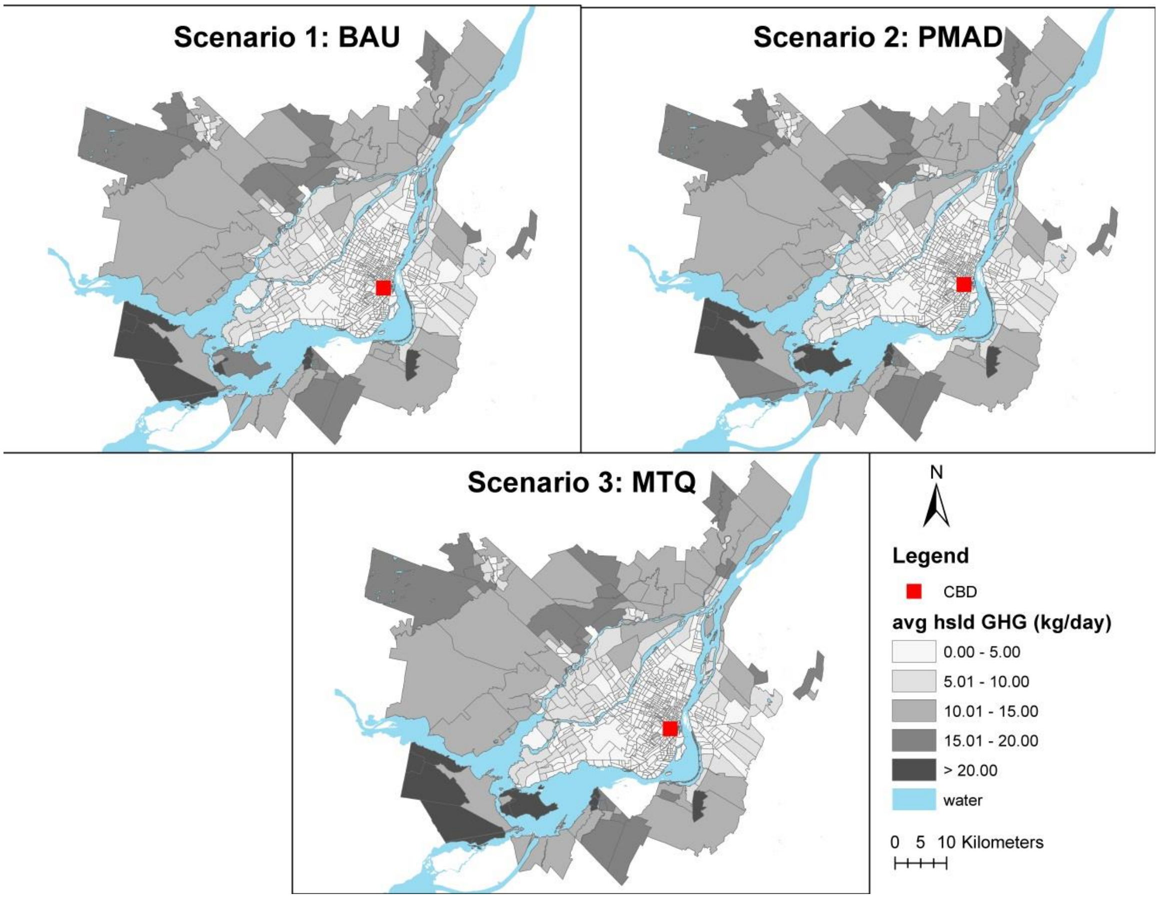
Second, across all scenarios, it can be found that more central regions experience the largest reductions in average CO_2 emissions between 2008 and PMAD scenario for 2031. The region of Longueuil experiences the greatest average annual reduction of 3.1 percent. Meanwhile, the Island of Montreal experiences 2.6 percent, Laval experiences 2.0 percent, North Shore experiences 1.3 percent, while South Shore only experiences 0.4 percent reduction between 2008 and the PMAD scenario in 2031. In the PMAD scenario, these reductions can be explained by the planned extension of transit lines, and the consequent high-density TOD areas, especially in the Island of Montreal, Laval and Longueuil. In other regions, the reductions can be attributed to PMAD's initiative of efficiently allocating growing population.

The final step of this research was to forecast CO_2 emissions for the entire metropolitan area. This was achieved by aggregating the predicted average household CO_2 emissions by census tract from region-specific models. The results of the aggregation is shown below in Table 2-18 and visually presented in Figure 2-3.

Table 2-3 Summary of CO_2 emissions for different scenarios in 2031

Variable	BAU 2031	PMAD 2031	MTQ 2031
Average total CO_2 (car + transit) CO_2 (kg/day)	6.13	5.50	5.85
Number of households in census (millions)	1,867,014	1,867,182	1,785,849
Total CO_2 (in kt)	11,454	10,268	10,448

Figure 2-3 Average household CO2 emissions under different scenarios in 2031



2.7. Conclusion

There were two main objectives to this research: (i) to develop region-specific models to estimate average household CO_2 as a function of BE and SE characteristics; and (ii) to use these models to forecast future average household CO_2 emissions for three scenarios – business as usual (BAU), and in accordance to PMAD policies and MTQ population forecasts. We found that due to the positive changes to BE indicators in PMAD policy, the forecasted average household CO_2 emissions are significantly lower than those of other two scenarios. In all regions, we determined the trend of average household CO_2 emissions decreasing over time. This is explained by decreasing automobile mode share, technological innovations, newer car fleets, increased densities and accessibilities, etc. Moreover, we found that SE indicators such as average household income and number of employed individuals in the household are positively associated with household CO_2 emissions. Lastly, it was evident that the Ds of BE, which include density, diversity, design, destination accessibility, distance to transit, etc. have statistically significant associations with CO_2 emissions. From the results, it was evident that households that are surrounded by more accessible, dense built environments and are closer to the CBD produce significantly lower average CO_2 emissions, than those further from the CBD with lower accessibility, density, etc. All in all, from this study, we can conclude that sustainable development policies would appear to be effective for stabilizing and/or reducing net transport-related CO_2 emissions.

Some limitations and future avenues of this research include: (i) the FCR used for the calculation of CO_2 emissions do not directly reflect the vehicle fleet of the household but a more aggregated, FSA-level fleet inventory; (ii) technological innovation affecting CO_2 emissions, such as electrification of public transit lines were not considered during the forecasts; (iii) due to the different survey period intervals, census data (SE) and O-D survey were matched disregarding 2 year gap; (iv) the boundary of the study region (greater metropolitan area) remained unchanged for this research, while in reality, this region is most likely to grow; (v) the effect of spatial autocorrelation was not captured.

3. Exploring the evolution of the effects of neighborhood typologies on cycling

3.1. Introduction

Cycling has been praised for its ability to achieve short to medium utilitarian trips while essentially producing no externalities, but instead, a handful of benefits. In recognition of these benefits, there has been a shift of focus away from motorized travel and towards the promotion of cycling in the fields of academia and policy making. Several countries namely Denmark, Germany, Switzerland and Netherlands have been particularly enjoying the cycling boom and the consequent benefits (Pucher et al, 1999). Meanwhile in Canada and the USA, cycling has remained as a marginal mode of transport, occasionally used for recreational purposes but rarely used for practical, everyday travel needs (Pucher and Buehler, 2008). While the levels of utilitarian cycling in no large North American city are comparable to those in Europe, Montreal is generally regarded as the North American leader (Larson and El-Geneidy, 2011). In 2009, BIXI, the largest public bicycle share program in North America was implemented, with 5050 bicycles at 405 docking stations by 2012. The current cycling facilities of the Island of Montreal include 425 km, comprising of 264 km off-street and 161 km on-street (Larson and El-Geneidy, 2011).

In this study, we focus our attention to utilitarian uses of cycling, specifically for home-based work trips. Similar to Wardman et al. (2007) and Caulfield (2014), the commuting market was selected because it represents a significant portion of trips which occurs at peak hours when the externalities of private vehicle use are at their worst. Furthermore, the characteristics of commute trips are relatively stable over time, and thus, time-series analysis of mode choice can be executed without the need to consider the more uncertain and complex issues surrounding the generation of new trips (Wardman et al. 2007). The modal share of cycling for commute trips is 1.4% and 2.8% on the Island of Montreal and up to 2.8 and 5.3% in central districts in 1998 and 2008, respectively.

In this paper, we aim to explore how cycling modal share for commuting has changed in different neighborhood types during the study period, between 1998 and 2008. In other words, we are interested in the evolution of neighborhood effects on individuals' likelihood to cycle to work. The neighborhood effects are the sum of the effects of the built environment and attitudes towards cycling. Generally, built environment indicators that have been found to influence cycling, which include land use mix and street network design have not changed significantly during the study period. Therefore, we expect that attitudinal changes are responsible for a great portion of the various changes in cycling between neighborhood typologies over time. In this study, we use three main methodological approaches to explore the effects of neighborhood type on cycling; (i) a binary logit model; (ii) a simultaneous equation model; and (iii) propensity score matching. While the former does not account for residential self-selection bias, the two latter approaches do.

The paper begins with a literature review regarding variables that affect cycling behavior as well as each of the methodologies used in transportation research. This is followed by the explanation of the data, variables and modelling approaches adopted for the research. Then, the results of the each of the different approaches are presented. The paper finishes with the reiteration of key findings as well as some avenues for future research.

3.2. Literature Review

There is a vast body of literature exploring the relationship between the built environment and travel behavior. A branch of this literature specifically focuses on the impact of the neighborhood characteristics of one's residential location on one's travel behavior including mode choice. There is a general consensus that a set of neighborhood characteristics create a more 'walkable' or 'cycle-friendly' neighborhoods. The 3 D's of the built environment first coined by Cervero and Kockelman (1997) include density, diversity and design. Neighborhoods with higher densities (population, employment), greater diversities (land use mix) and better design (cycling lanes, sidewalks, link to node ratio) have been found to be associated with less vehicle-miles travelled (VMT) and more active and public transportation. The original 3 D's have been complemented with two additional D's which are distance to transit and destination accessibilities (Cervero et al. 2009). In their study of mode choice of residents in San Francisco Bay Area, Cervero and Kockelman (1997) found that having retail activities within neighborhoods was most closely associated with non-personal vehicle mode for work trips. For the same study region, Cervero et Duncan (2003) found that urban design and land-use diversity factors were positively associated with the decision to ride a bicycle. In fact, mixed land uses and balances of residences, jobs and retail services worked in favor of cycling. Furthermore, they found that the influence of employment density was less straightforward. At the 1-mile radius of an individual's origin, higher employment density encouraged cycling, however, the opposite effect was seen at the 5-mile radius. Cervero and Duncan (2003) presume that this is due to the fact that dense employment settings, like urban job centers and edge cities often create numerous roadway conflict points and safety hazards for cyclists.

At the same time, Cervero et al. (2009) found that built environment design, specifically street density and connectivity strongly influence active mode choice of residents in Bogotá, Colombia. The model revealed that a Bogotá resident is nearly twice as likely to cycle for utilitarian purposes for 30 minutes or more per weekday, in a setting with relatively high street density than in a low density setting. In Bogotá, it was also found that bike-lane density did not significantly influence utilitarian cycling. This is surprising as there is empirical evidence suggesting that the presence of sidewalks and bicycle paths increase walking and cycling trips, respectively (Kitamura et al. 1997). The discrepancy in the two studies may be due to the quality of the active transportation infrastructure as well as the perspectives of residents on the importance of the infrastructure.

Relative to other modes of travel, cycling is especially sensitive to physical conditions of the trip-maker, trip characteristics, and his physical environment. Such limitations along with many others, such as elevation changes, weather, and personal health do not play a prevalent role in determining motorized travel. Therefore, methodological refinements tailored to cycling are necessary to accurately capture the actual effect of the built environment (Winters et al. 2010). The physical and socio-demographic conditions of the trip-maker that have been found to influence the likelihood to cycle include age, gender, disabilities, auto ownership and presence of children. The majority of previous research suggests age to have a negative linear relationship with cycling (Plaut, 2005; National Highway Traffic Safety Administration and Bureau of Transportation Statistics, 2008). However, Moudon et al. (2005) found a curvilinear relationship between age and cycling where age category of 25 to 35 years is more likely to bicycle than the youngest age category of 18 to 21 years old. Another trip characteristic that has been studied is the time of departure. The results for departure time in Caulfield's (2014) study of Dublin demonstrate that individuals living in areas that have experienced an increase in cycling have later departure times than those living in areas with no change in cycling levels. In another study, Winters et al. (2010) used travel data of current and potential cyclists of Metro Vancouver to explore the influence of the built environment on mode choice, specifically cycling versus driving. A multilevel logistic regression was used to model the likelihood that a trip was made by a bicycle, while adjusting for trip distance and personal demographics. The built environment characteristics were considered at three spatial zones: trip origins, trip destinations and along the route. They found that the odds of cycling were associated with less hilliness, higher intersection density, less highway and arterials, higher population density and greater land use mix. Although different factors were found to be significant within each spatial zone, the built environment of the routes (250 m buffer) were found to be more influential than that in the origins and destinations.

The specification of appropriate calculations of built environment indicators may be a challenge in cycling research. In order to capture the built environment of the trip-maker's residence, circular and road network buffers have often been applied around the residential location (Oliver et al. 2007). However, as our research focuses on the effects of neighborhood types, neighborhood typologies needed to be defined. Harding et al. (2012) have developed a methodology to generate neighborhood typologies based on important built environment indicators, such as population and employment densities, land use mix and public transit accessibilities. The objective of this neighborhood typology clustering is to assemble observations into subgroups which share similar built environment characteristics. The clustering method allows maximum inter-cluster variation while minimizing intra-cluster variation (Zahabi et al. 2012). A few researchers have adopted this methodology to compare the land-use and neighborhood effects on travel behavior (Lin and Long, 2008; Miranda-Moreno et al. 2011; Riva et al. 2008; Zahabi et al. 2012).

In conventional transportation planning practice, a one-way causal flow of the effects of land use pattern on travel behavior if often assumed (Pinjari et al. 2007). This implies that households and individuals first locate themselves in neighborhoods then their travel behavior is shaped by neighborhood attributes. In the context of our study, the above reasoning implies that the observed differences in cycling for commuting purposes are directly caused by their neighborhood typologies. However, in reality, individuals and households choose to live in certain neighborhoods that allow them to pursue their activities using modes that are compatible with their socio-demographics and travel preferences (Pinjari et al. 2007). Specifically, it has been found that there are significant observed factors contributing to residential self-selection, including auto and bicycle ownership, income, household size and race (Pinjari et al. 2007). In the field of travel behavior, the majority of studies are based on observational data, in which the respondents self-select to live in, rather than being randomly assigned into different environments (Cao et al. 2010). Thus, comparing travel behavior of two different neighborhood typologies without controlling for residential self-selection tends to produce a biased estimate of the influence of the built environment on travel behavior.

Many approaches have been proposed to tackle the notion of residential self-selection. Cao et al. (2009) reviewed the methodologies of 38 empirical studies which address the effect of residential self-selection on travel behavior. The authors categorized the studies into nine methodological approaches; (i) direct questioning; (ii) statistical control; (iii) instrumental variables; (iv) sample selection; (v) propensity score; (vi) joint discrete choice models; (vii) structural equations models; (viii) mutually dependent discrete choice models; and (ix) longitudinal designs. Every quantitative study reviewed in Cao et al. (2009) have identified a statistically significant influence of one or more built environment measures on travel behavior indicator of interest even after accounting for residential self-selection. The authors clarify this phenomenon by illustrating an example of two individuals. If an individual who is characterized by walking-oriented moves to a walking-oriented environment, we expect him to walk more. But, it is also probable that if an individual who is auto-oriented moves to a walking-oriented environment, we also expect her to walk more.

For exploring the effects of the built environment on mode choice, researchers often adopt logit models (Cervero and Duncan, 2003; Heinen et al. 2012; Moudon, 2005; Plaut, 2005). The results from these models can demonstrate the effect sizes of each variable included in the model on mode choice. In fact, many of previous literature have reported a significant impact of neighborhood attributes in mode choice decisions (Ewing and Cervero, 2001; Kockelman, 1997; Pinjari et al. 2007). Most models do not account for residential self-selection. However, there are exceptions in literature where residential self-selection is accounted for in exploring travel behavior. In binary logit models explaining mode choice, the effect sizes of each of the included explanatory variables can be determined. These effect sizes represent the influence on mode choice while controlling for other explanatory variables. However, the results of binary logit models are not able to capture the effect of residential self-selection. In another study by Schwanen and Mokhatarian (2005), the authors investigated to what extent commute mode choice differs not only by residential neighborhood but also by the presence and level of mismatch between a commuter's current and preferred type of neighborhood. Instead of a binary logit model, a multinomial logit analysis was performed in which socio-demographic characteristics, mobility limitations, personality factors and lifestyle types were included as control variables. They found that both residential self-selection and neighborhood effects significantly influence commute mode choice.

An econometric modelling approach to account for self-selection is the use of simultaneous equation models (SEM). SEMs simultaneously model can be used to model the choice of residential neighborhood and the mode choice jointly, thus accounting for residential self-selection. In a study of the San Francisco Bay Area, Cervero and Duncan (2002) explored the self-selection question by constructing a three-tiered model of residential self-selection, vehicle ownership, and mode choice. The nested logit model structure is hierarchial and sequential. As a result, the residential location influences car ownership, and car ownership influences mode choice. They found that the impact of neighborhood attributes on rail commuting significantly decreased after controlling for residential self-selection. Zahabi et al. (2012) adopts a simultaneous equation model (SEM) to simultaneously model the following: (i) neighborhood choice as a function of socio-demographic characteristics; and (ii) mode choice as a function of neighborhood choice, parking management strategies and socio-demographics. They found that the neighborhood type where commuters live plays an important role in the transportation mode choice even after controlling for self-selection, socio-demographics and transit attributes. Similarly, Miranda-Moreno et al. (2011) developed a SEM to take into account interactions between vehicle ownership and choice of residential location as an explanatory endogenous variable for total distance traveled by respondents. They concluded that the SEM better explains distance travelled than a simple linear regression model.

The propensity score matching method (PSM) is another approach to statistically take residential self-selection into account to estimate neighborhood effects. Essentially, PSM allows the pairing of observations from treatment and control groups based on their propensity to choose to be a member of the treatment group. So far, there have been a few studies adopting PSM including studies to disentangle the effects of the built environment and self-selection on travel behavior (Cao et al. 2010; Cao and Fan, 2012; Forsyth et al., etc.). These studies attempt to control for the influence of self-selection to appropriately discount the effect of the built environment on various aspects of travel behavior such as vehicle miles driven, driving duration and transit duration. Using data collected from North Carolina's regional travel survey, Cao and Fan (2012) find that upon removal of self-selection bias, high-density neighborhood residents travel 3.31 fewer miles per person per day on average than their counterparts in low-density neighborhoods. Depending on the travel behavior variable of interest, self-selection accounts for 28% to 64% of the observed influences. In another study by Forsyth et al. (2008), PSM is applied to explore the relationship between active transportation and the built environment, specifically design and destinations. The study uses PSM to match participants in across four comparison groups (high/low density and large/small block size) according to their estimated propensity scores which were estimated by a logistic regression model. The covariates added to the model were socio-demographic characteristics of the participants. Contrary to prior research, the authors find that socially similar people achieve the same total amount of physical activity in different places.

In this research, we adopt three different models to explore the effects of neighborhood type on the propensity to cycle to work over time, with two of these methods accounting for residential self-selection. Although to varying extents, each of the three models (binary logit model, simultaneous equation model, and propensity score matching) have been used in travel behavior research. Some of this research tries to use these models to take residential self-selection into account. However, there is no research exploring the evolution of the neighborhood effects over time using these models. In this research, we use three different methodologies to try to answer the same question – how has the probability of cycling changed over time in different neighborhood types? By looking at the consistencies and variations in the results of these models will allow us to confidently answer this question.

3.3. Methodology

3.3.1. Travel Data

An origin-destination (O-D) travel survey of Metropolitan Region of Montreal for 1998, 2003 and 2008 were used for travel data. The O-D survey, which takes place every 5 years, provides urban travel information for an average weekday for residents of Montreal (AMT, 2008). The survey is designed to reflect travel in the autumn as 1998, 2003 and 2008 surveys were conducted from August 25th to December 18th, September 3rd to December 20th, and September 3rd to December 18th, respectively. Through a telephone interview, participating households provide detailed information for every trip made during the previous day by every member of the household over the age of 4. For each trip, the following information is provided: x-y coordinates of origin, destination and residence, mode(s) of travel, purpose of trip, socio-demographic characteristics of individual and his household, time of departure, expansion factor of individual, etc.

As this study focuses on cycling behavior on the Island of Montreal, only individuals residing on the island were included. Furthermore, we were specifically interested in commute trips to work, and thus, only included individuals who were either full- or part-time employees and made a work-related trip during the survey period. The mode choice of the individual reflected the mode of their first home-based commute trip in the day. The selected individuals for this study included a total number of 21,188, 20,170, and 19,508, in 1998, 2003 and 2008, respectively. Upon consideration of trip-level expansion factors, 1.4%, 1.9%, and 2.8% of trips were made by bicycle in 1998, 2003, and 2008.

3.3.2. Socio-demographic Variables

In our analyses, we included two sets of socio-demographic variables. One set is used to explain residential choice, while the other set explains mode choice of commute to work. Household-level socio-demographic characteristics that we included are automobile ownership and household size. Auto ownership has been found to negatively affect cycling modal share (Cervero and Duncan, 2003; Plaut 2005). Individual-level characteristics that have been included in the models are age, sex, and employment status. In previous studies, being male has consistently been found to be positively associated with cycling (Heinen et al. 2013; Plaut, 2005; Cervero and Duncan, 2005). Also, most studies have found that being young (less than 35 years old) is positively associated with cycling (Heinen et al. 2013; Titze et al. 2008). Employment status has rarely been included in cycle mode choice models in previous literature. However, we were determined to see if individual's employment status (full-time or part-time) was statistically significant in explaining the decision to ride a bicycle to work. Table 3-2 shows the summary statistics for each of the socio-demographic characteristics of the commuters included in the study.

3.3.3. Built Environment Indicator Generation

This study adopted a methodology developed by Harding et al. (2012), which applies a weighted 500 meter grid system to calculate built environment indicator values at the cell-level. A total of five built environment indicators were included in this study; (i) population density; (ii) employment density; (iii) cycling network density; (iv) public transit accessibility; and (v) land-use mix. Upon compilation of the cell-level built environment indicators, neighborhood typologies were generated using a k-means cluster analysis. In order to evaluate trends over time, neighborhood clusters were held constant, and all variables included in the clustering process reflected values of the most recent period, 2008.

A 500 by 500 meter grid was created using 'Create Fishnet' tool under Data Management in ArcGIS 10.1. Calculating the indicators at the grid cell-level minimizes the potential of distorted results associated with scale and modifiable areal unit problems (Harding, 2012; Yeh and Li; 2001). Weights were applied to average cell values using surrounding contiguous cells to avoid peaks in the same way as seen in Harding (2013) and Harding et al. (2012).

Population and employment densities: Similar to the O-D travel survey, the collection of data for the Canadian Census occurs every 5 years. We used the population and employment count data at the census-tract level from Statistics Canada for census year, 2006. The population counts were assigned to the portion of census tracts occupied by residential land use, and job counts to commercial, industrial and institutional land uses, which allowed us to calculate the net densities (Harding et al. 2012). The densities were simply calculated as the population/employment counts per square kilometer of land. Population and employment densities have been found to be positively associated with cycling levels (Parkin, 2008; Winters et al. 2010; Pinjari et al. 2007).

As a result, we expect individuals living in neighborhood typologies with high density measures, such as downtown (1), urban (2), and to some extent urban-suburb (3) to experience a higher likelihood to cycle to work than those in other neighborhoods.

Cycling network density: Cycling infrastructure data was obtained from Ville de Montréal and Vélo Québec. The included cycling infrastructure only reflects the bicycle lanes and trails on street network as well as in greenspace including parks. Some revisions were made to ensure accurate reflection of the cycling infrastructure in the respective years in ArcGIS 10.1. In previous literature, bicycle lane densities have been found to be positively associated with cycling levels (Pinjari et al. 2011). The central areas of Montreal have relatively high cycling network densities, thus, we expect individuals living in these neighborhoods to cycle more.

Public transit accessibility: Transit accessibility was calculated by first finding the nearest bus, metro and rail line stations to the centroid of each grid cell. Then, the contribution of each line's closest stop was summed (Zahabi et al. 2012; Harding et al. 2012). As a result, a transit stop that was closer from the centroid of the grid cell of interest or had a smaller headway would increase the transit accessibility for that grid cell. The public transit network for Montreal was built up as a hybrid network. It is composed of a base originally geocoded in TransCAD by Dr. Murtaza Haider of Ryerson University in 2003, upon which additional lines were added to cover the extent of Greater Montreal. While, the off-island transit lines were subsequently added by hand in the summer of 2011. Public transit accessibility has rarely been included in models explaining cycling mode choice. We were curious to determine the relationship between transit accessibility and cycling. A significant portion of neighborhoods in Montreal that have high transit accessibilities are transit-oriented developments (TODs). In many cases, the design of TODs not only encourages transit use but also active transportation.

$$PTaccess_j = \sum_{i=1}^{n} \left(\frac{1}{d_{ij} \times h_i} \right) \qquad \text{(Eq. 3-1)}$$

Where:

$PTaccess_j$ = public transit accessibility at cell *j*

d_{ij} = distance (km) from the centroid of cell *j* to nearest stop of the bus, metro, or rail line *i* (minimum value of 0.1 km)

h_i = average headway (hours) of line *i* during AM peak (maximum value of 1 hour)

<u>*Land use mix:*</u> A land use shapefile provided by Desktop Mapping Technologies Inc. (DMTI) was used to calculate the entropy index. Out of the seven land use categories defined in the data, only five categories were considered for the calculation; (i) which are residential; (ii) commercial; (iii) institutional and governmental; (iv) resource and industrial; and (v) park and recreation. The categories that were not included in the calculation are water and open area (Zahabi et al. 2012). The following equation was used. Land use mix at the origin of the trip has been found to be positively associated with cycling levels (Cervero and Duncan, 2003; Winters et al. 2010; Pinjari et al. 2011). As a result, we expect urban neighborhoods that have high land use diversities to have higher levels of cycling.

$$E_j = \sum_{i=1}^{n} \frac{[\left(\frac{A_{ij}}{D_j}\right) \ln(\frac{A_{ij}}{D_j})]}{\ln(n)} \qquad \text{(Eq. 3-2)}$$

Where:

E_j = entropy index for cell j

A_{ij} = area of land use i in cell j

D_j = area of cell j excluding water and open area

n = number of land use categories (in this study, n=5)

3.3.4. Neighborhood typology

Similar to Harding et al. (2012), a k-means clustering technique was used in STATA 11.1 in order to generate neighborhood typologies based on the previously defined built environment indicators. Calinski-Harabasz values for each number of clusters (k) between 2 to 8 were calculated. The highest value indicates a statistically optimal number of clusters, where between-cluster sum of square is maximized, while minimizing both within-cluster sum of squares (Milligan and Cooper, 1985; Harding, 2012). In our study, the optimal number of clusters was found to be k=5. A map of the distribution of the clusters is presented in Figure 3-1 and the built environment characteristics for the neighborhood typologies are demonstrated in Table 3-1. The clusters can be characterized according to five indicators as follows:

Downtown (1) is characterized by best public transit accessibility, highest employment density, greatest land use mix, highest cycling network density, and relatively high population density. This area comprises of the central business district and directly neighboring regions.

Urban (2) has the highest population density as well as a relatively high employment density, land use mix, and public transit accessibility. Surprisingly, the cycling network density for this region is quite low relative to other neighborhood typologies.

Urban-suburb (3) consists of moderate densities, land use mix and public transit accessibility. The cycling network density of this neighborhood typology is the lowest in the study area.

Inner suburb (4) is characterized by relatively low densities, land use mix and public transit accessibility. The cycling network density for this region is surprisingly not low.

Outer suburb (5) includes areas with lowest densities, land use mix and public transit accessibility. This neighborhood typology represents the most peripheral regions of the island with moderate cycling network density.

Table 3-2 demonstrates the summary statistics of socio-demographic characteristics of trip-makers for each of the neighborhood typologies. Table 3-3 demonstrates the cycling, walking and active transport modal share for each of the neighborhood typologies. It is surprising to see that neighborhood type 'urban (2)' has the highest cycling levels, while 'downtown (1)' has lower cycling levels than the mean levels of the entire Island of Montreal (Table 3-3). The low cycling levels in 'downtown (1)' are explained by very high walking mode share. It is important to note that in all neighborhood types, cycling and walking levels have increased during the study period. However, 'downtown (1)' and 'outer suburb (5)' neighborhoods have experienced the smallest change in cycling levels.

Figure 3-1 Neighborhood typologies

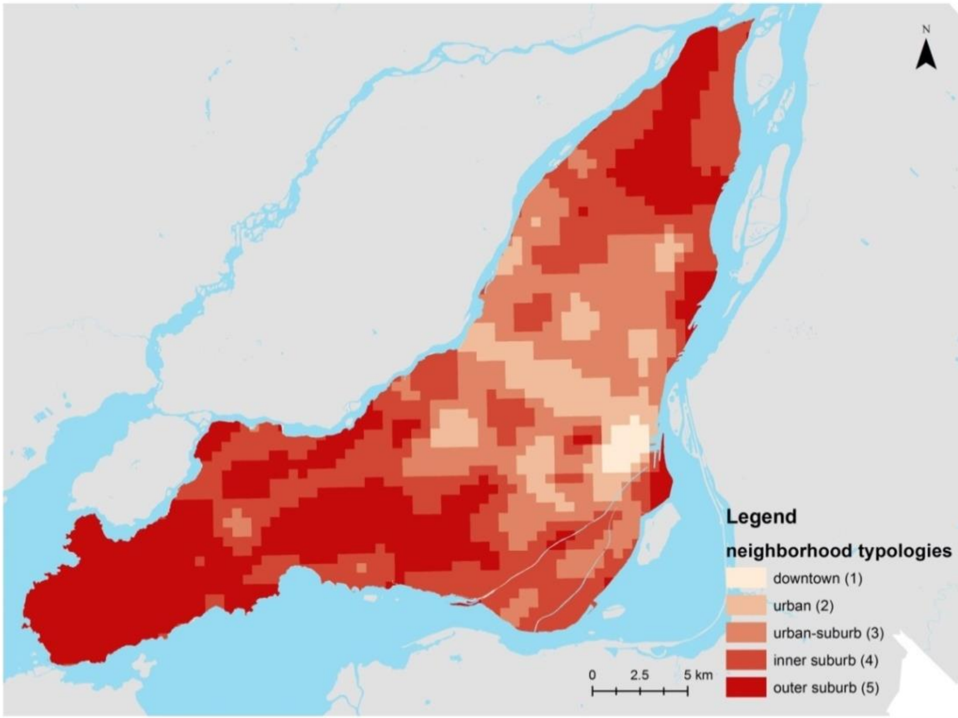


Table 3-1 Modal share of walking and cycling on Island of Montreal

	downtown (1)				urban (2)				urban-suburb (3)				inner suburb (4)				outer suburb (5)				Island of Montreal			
Variable	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)
Cycling	1.2	1.0	1.5	0.3	2.8	3.5	5.3	2.5	1.4	2.3	3.0	1.6	0.6	0.8	1.1	0.5	0.8	0.5	1.0	0.1	1.4	1.9	2.8	1.4
Walking	33.2	40.4	35.3	2.1	10.3	10.9	13.5	3.1	6.2	7.0	8.0	1.8	3.2	4.0	3.8	0.6	2.0	2.0	2.6	0.6	6.4	7.1	8.1	1.7
active transportation	34.4	41.4	36.8	2.4	13.1	14.4	18.7	5.6	7.5	9.3	11.0	3.5	3.8	4.8	5.0	1.2	2.8	2.5	3.5	0.8	7.8	9.0	10.9	3.1

Table 3-2 Summary statistics of socio-demographic characteristics of trip-makers

	downtown (1)				urban (2)				urban-suburb (3)				inner suburb (4)				outer suburb (5)				Island of Montreal			
Variable	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)	1998 (%)	2003 (%)	2008 (%)	Δ (%)
auto ownership																								
0 car per adult in HH	43	43	35	-8	28	27	30	2	19	21	20	1	8	9	8	0	2	2	3	1	16	17	17	1
0 to 1 car per adult in HH	34	35	40	5	49	49	47	-2	52	48	51	-1	54	51	51	-3	42	40	43	1	50	48	49	-1
1 car per adult in HH	22	20	25	4	22	22	22	-1	28	29	27	-1	37	37	37	1	52	53	49	-3	32	33	31	-1
more than 1 car per adult in HH	1	2	0	-1	1	2	1	0	1	2	2	1	2	3	4	2	4	5	5	1	2	3	3	1
household size																								
single-person HH	33	31	27	-6	20	20	20	0	16	18	16	0	10	11	11	1	6	6	4	-1	14	15	14	0
non-single person HH	67	69	73	6	80	80	80	0	84	82	84	0	90	89	89	-1	94	94	96	1	86	85	86	0
gender																								
Male	58	57	60	2	56	54	52	-4	54	53	52	-2	55	54	51	-4	58	56	53	-5	55	54	52	-3
female	42	43	40	-2	44	46	48	4	46	47	48	2	45	46	49	4	42	44	47	5	45	46	48	3
Age																								
15 to 24 yrs old	11	8	4	-7	11	9	5	-6	10	9	5	-5	8	7	6	-2	6	7	6	0	9	8	5	-4
25 to 34 yrs old	35	33	28	-6	31	31	27	-4	28	27	23	-5	24	22	17	-8	20	17	12	-8	27	25	21	-6
35 to 44 yrs old	26	22	19	-7	29	26	25	-4	29	27	25	-4	31	27	25	-6	33	30	24	-9	30	27	25	-5
45 to 54 yrs old	20	22	27	7	21	23	26	5	23	25	30	7	25	30	33	8	30	32	36	7	24	27	31	7
55 yrs old and older	9	15	22	13	7	11	16	9	10	12	18	8	11	13	19	8	12	14	22	10	10	12	18	8
employment																								
full-time employee	95	91	93	-2	92	93	92	0	93	93	92	-1	93	93	93	0	93	93	93	0	93	93	92	0
part-time employee	5	9	7	2	8	7	8	0	7	7	8	1	7	7	7	0	7	7	7	0	7	7	8	0

Table 3-3 Characteristics of neighborhood typologies

	downtown (1)			urban (2)			urban-suburb (3)			inner suburb (4)			outer suburb (5)			Island of Montreal		
Variable	1998	2003	2008	1998	2003	2008	1998	2003	2008	1998	2003	2008	1998	2003	2008	1998	2003	2008
population density (ppl/km^2)	83.40	82.51	77.28	94.51	94.91	94.94	79.85	81.20	78.85	46.97	46.16	45.21	26.23	26.79	25.32	68.86	69.11	67.27
employment density (ppl/km^2)	311.66	321.38	341.18	52.53	53.26	58.46	24.70	24.75	24.66	12.22	12.22	12.88	6.74	6.75	7.32	31.51	31.05	33.59
entropy index (ppl/km^2)	0.62	0.62	0.63	0.54	0.54	0.54	0.48	0.48	0.48	0.38	0.38	0.37	0.26	0.25	0.25	0.45	0.45	0.44
public transit accessibility	508.18	514.81	530.32	333.23	332.45	336.34	211.74	212.00	211.19	120.58	120.88	121.22	55.55	55.45	53.45	204.71	203.36	203.85
cycling network density (km/km^2)	7.91	7.97	8.08	3.85	3.88	4.22	3.01	3.06	3.24	5.16	5.26	4.99	4.17	4.27	4.17	4.03	4.07	4.17
no. of observations	463	392	374	4383	4349	4196	7235	7113	7012	6370	5870	5879	2737	2446	2047	21,188	20,170	19,508

3.3.5. Cycling-specific Built Environment Variables

Intersection (node) density: A shapefile of street network of Greater Montreal provided by Desktop Mapping Technologies Inc. (DMTI) was used to calculate road network density, design, and connectivity variables. In the field of transportation planning, there are three types of nodes to consider; (i) real nodes; (ii) dangle nodes; and (iii) nodes. Real nodes are intersections, which can be defined as endpoints of links that connect to other links (Dill, 2004). Whereas, dangle nodes are endpoints of links that have no other connections as they are dead-ends or cul-de-sacs. Nodes encompass both real and dangle nodes. In this study, we excluded dangle nodes and instead, were only interested in real nodes. Intersection density was calculated as the number of intersections (real nodes) per square kilometer of land.

Street density: Street density was simply calculated as the number of linear kilometers of streets per square kilometer of land. A higher value would indicate more intersections and presumably, higher connectivity (Dill; 2004).

Link to node ratio: Link to node ratio was calculated by dividing the number of links by the number of intersections (real nodes).

Distance to cycling infrastructure: In ArcGIS 10.1, we calculated the tangent distance in kilometers to the nearest cycling lane from individuals' residence. The greater the distance, we assume that the likelihood to cycle decreases.

3.3.6. Trip Characteristics

Commute distance: From the O-D travel survey data, we obtained the XY coordinates of the individuals' household locations and work-related destinations. The first home-based work-related trip of the day was used to derive the destination coordinates. The two sets of coordinates were used to calculate an airline distance. In cycling studies, trip distance has been found to be negatively associated with cycling (Heinen et al. 2013; Cervero and Duncan, 2003).

Departure Time: Departure times were obtained from the O-D travel survey data. The departure time of the first home-based work-related trip of the day was used. This variable has not been included often in previous cycling research. One of the few studies that has included departure times is Caulfield (2014)'s study on cycling in Dublin. His results indicate that commuter cyclists that live in neighborhoods that have experienced increase in cycling levels generally depart later to work.

3.3.6. Model Calibration

We used three types of models to explore the effects of neighborhood typologies on cycling; (i) a simple binary logit model; (ii) a simultaneous equation model; and (iii) propensity score matching model. The purpose of including three types of models was to determine if the effects of neighborhood typologies change significantly when residential self-selection is taken into account. The binary logit model allowed us to quantify the effects of neighborhood typologies on cycling levels as well as its evolution while controlling for socio-demographics, trip characteristics and cycling-specific built environment variables. The binary logit model does not take residential self-selection into account, while the two latter models do. The second type of model used was simultaneous equation model (SEM), which allowed us to simultaneously model the choice of residential neighborhood and the choice of mode as a binary outcome (bicycle or other modes). That is, individuals select simultaneously where to live and what mode of transport they use for their home-based work trips. The third model, propensity score matching (PSM) allowed us to estimate the true effect of neighborhood type on cycling while controlling for residential self-selection. The PSM process matched individuals between neighborhood typologies based on their propensity scores to select to live in certain neighborhood typologies. In this section, we will explain the steps taken to estimate each of the models.

3.3.6.1. Binary Logit Model

Two binary logit models were estimated, where one model investigates the effects of neighborhood typologies and year separately (Figure 3-2), and the other explores the cross effects of neighborhood typologies and year (Figure 3-3). The results of the first model were expected to answer two questions; (i) what are the effects of neighborhood types on cycling over the entire study period, while controlling for other explanatory variables?; and (ii) how has cycling evolved over the study period? Meanwhile, the results of the second binary logit model were expected to explain the evolution of neighborhood effects on cycling for each of the neighborhood typologies. In both models, the reference neighborhood typology and year were set as urban-suburb (3) and 1998, respectively. Tables 3-5 and 3-6 present the model results.

Figure 3-2 Configuration of binary logit model - separate neighborhood typologies and year effects

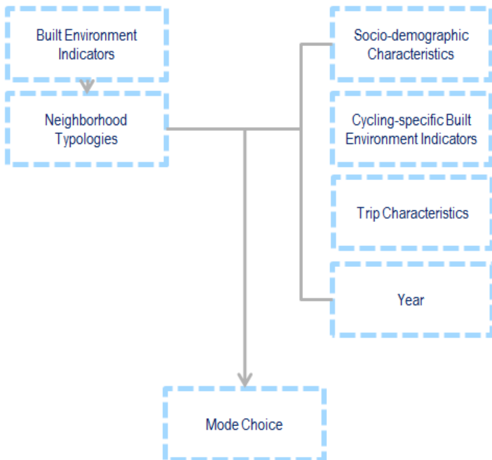
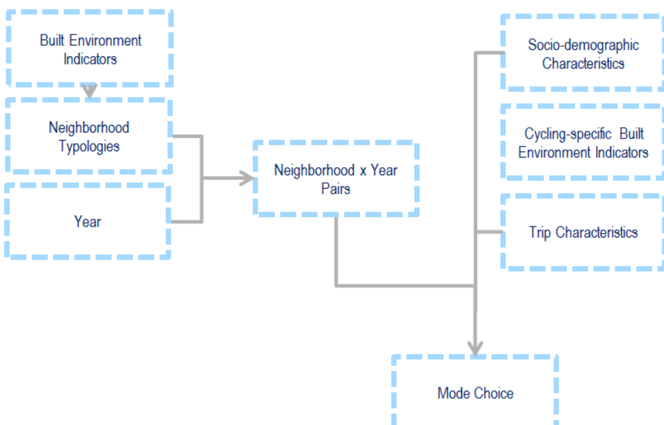


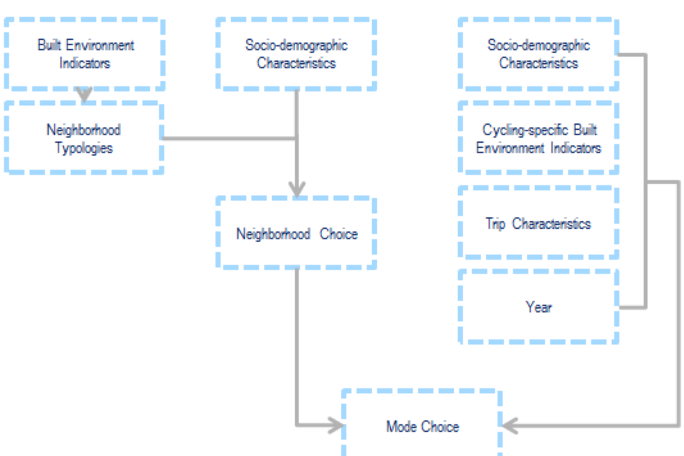
Figure 3-3 Configuration of binary logit model - paired neighborhood typologies and year effects



3.3.6.2. Simultaneous Equation Model

We adopted the methodological approach used by Zahabi et al. (2012) for the simultaneous equation model (SEM). According to the five neighborhood typologies previously defined and whether the individual cycled to work or not, five different alternatives were set up for residential location and two for mode choice. In our model, neighborhood choice was a function of household-level socio-demographic characteristics, whereas mode choice was directly influenced by neighborhood type, individual-level socio-demographic characteristics, cycling-specific built environment indicators, and trip characteristics as shown in Figure 3-4. Equations 1 and 2 present the utility functions for the different choices, taking into account the phenomenon of residential self-selection between household location choice and mode choice. The model was estimated using the command 'mtreatreg' in STATA 10.1. This estimation method allowed the modeling of multinomial treatments and a binary outcome using maximum simulated likelihood (Deb and Seck, 2009; Deb and Trivedi, 2006). For this study, the mode choice variable was represented as a binary outcome while the treatment choice (neighborhood typologies) was assumed to follow (conditionally on the latent factors) a mixed multinomial logit (MMNL) structure defined in Equation 3, with the normalization structure $\beta_3 = 0$ and $j = 1,2,3,4,5$. The final outcome variable, mode choice had a logistic distribution in this model. The SEM considered household location choice as an endogenous choice as well as a factor explains mode choice by individuals, thereby taking into account potential self-selection bias.

Figure 3-4 Configuration of simultaneous equation model



$$M_{qi} = \alpha_q x_{qi} + \sum_{j=1}^{5} \mu_j k_{ij} + \sum_{j=1}^{5} \lambda_j l_{ij} + \varepsilon_{qi}$$

(Eq. 3-3)

$$N_{ij} = \beta_i z_i + \delta_j l_{ij} + \eta_{ij}$$

(Eq. 3-4)

$$\Pr(K_{ij} | x_i, l_{ij}) = \frac{\exp(\beta_j z_i + \delta_j l_{ij})}{\sum_k^j \exp(\beta_k Z_i + \delta_k l_{ik})}$$

(Eq. 3-5)

M_{qi}: utility function of mode choice of individual *i* (q = 1 for cycling, q = 0 for other modes)

N_{ij}: utility of cluster choice *j* for individual *i*, *j* = 1,2,3,4,5

x_i: socio-demographic and trip characteristics of individual *i*

z_i: socio-demographic characteristics of individual *i* associated with neighborhood typology choice

k_{ij}: dummy variables representing neighborhood cluster j for household of individual *i*

l_{ij}: latent explanatory variable of unobserved heterogeneity by endogenous variables

ε_i: random independent error (logistic distribution)

η_{ij}: random independent error (logistic distribution)

$\alpha, \beta, \delta, \lambda, \mu$: model parameters (vectors)

3.3.6.3. Propensity score matching with multiple treatments

Another method that has been used to account for residential self-selection bias is propensity score matching (Cao et al. 2010). Propensity score matching was developed to overcome the fact that the assignment of subjects to treatment and control groups in observational data is not random, causal inferences achieved without controlling for confounding characteristics can be biased (Becker and Ichino, 2002). Similarly, origin-destination survey is categorized as observational data, where individuals are not randomly assigned to the neighborhoods that they live in. Instead, individuals choose to live in certain neighborhood types. To attend to this issue, Rosenbaum and Rubin (1983) introduced the method of propensity score matching (PSM), which brings a handful of advantages as it allows researchers to (i) closely mimic experimental study designs, (ii) increase transparency of inference, and (iii) minimize model dependence (Oakes and Johnson, 2006). The PSM model we have adopted is often referred to as PSM with multiple nominal treatments, meaning that it compares treatment effects between each pair of neighborhood types, where one is the control group and the other is treatment group (Lechner, 2002). The PSM process is repeated for each pair separately, where the number of pairs is 10 in our case (no. of pairs $=\frac{N(N-1)}{2}$, where N=5 is the number of neighborhood typologies). As our study included three periods of data, we repeated the PSM process for 30 different pairs. Propensity score (PS) is the conditional probability of receiving a treatment given pre-treatment characteristics (Rosenbaum and Rubin, 1983). PS can be estimated with a traditional logistic regression model (Oakes and Johnson, 2006). Furthermore, due to the fact that PS model was simply used for prediction purposes, we neither needed to check for statistical significance nor multicollinearity of independent variables (Cao et al. 2010). In our study, we estimated the propensity score, which is the probability of choosing to live in treatment over control neighborhood typology, given the socio-demographics of the individual's household. This was achieved by simply predicting the probabilities after estimating binary logit models. For illustration purpose, we used Pair G, where the control group is outer suburb (5) and the treatment group is urban (2) to demonstrate the steps. Table 3-9 displays the binary logit model for the choice of living in urban (2) relative to outer suburb (5).

Then, we adopted a methodology similar to Cao et al. (2010) to find an "identical" person from those living in urban (2) to match each person living in outer suburb (5). Using propensity scores, the observations were matched between treatment and control groups using a command in STATA called "PSMATCH2". The options of "common" and "caliper(0.01)" were used. The "common" option drops treatment observations with PS that are outside the range of PS of control observations prior to matching. The "caliper(0.01)" option limits matches in control observations to those with PS within 0.01 of the PS of the treatment observations. In using PSMATCH2, it is important to sort data randomly prior to matching in order to reduce bias. For Pair G, the PSMATCH2 process dropped 14 observations. The next step of PSM is to determine whether or not the matched individuals from treatment and control groups are systematically different. Similar to Cao et al. (2010), we used the command "PSTEST" in STATA to assess whether household socio-demographics are balanced between the matched groups. Standard differences of below 10 percent are generally considered to be the acceptable difference between groups (Oakes and Johnson, 2006; Cao et al. 2010). In cases where standard differences were above 10 percent, models were re-calibrated to bring the values down to the acceptable level. The pre- and post-PSM standard differences for 1998 are presented in Tables 3-10. The final step of PSM is to calculate the average treatment effect (ATE), which represents the average change in cycling behavior when a randomly selected person is moved from the control group to the treatment group. In the case of Pair G, the ATE is the average change in the likelihood to cycle for an individual that moves from outer suburb (5) to urban (2) neighborhood. The ATE is calculated as the difference between the mean cycling levels of the matched urban (2) individuals and outer suburb (5) individuals. This represents the true effect of neighborhood typologies, while controlling for residential self-selection. Table 3-11 demonstrates the ATE of each of the pairs in different years.

3.4. Results

3.4.2. Binary logit model

3.4.2.1. Robustness of models

The Akaike Information Criterion (AIC) values are presented in Table 3-4 to compare the robustness of each of the models used. The AIC value of the simultaneous model is smaller than the independent models (173 211.7 vs. 173 223.5). This indicates a better fit of the simultaneous equation model compared to the two separate logit models, thus justifying the use of the joint model

Table 3-4 Comparison of AIC

			LR test	
Methodology	Model Type	AIC	Coefficient	P-Value
Binary logit	Neighbourhood and year, separately	10 383	1 279	0.000
	Neighbourhood-year pairs	10 940	1 284	0.000
simultaneous model	Binary logit – mode choice	10 374	-	-
	MNL – cluster choice	162 849	-	-
	binary logit + MNL	173 224	-	-
	Simultaneous multinomial treatment model	173 212	6 817	0.000

The results of the binary logit models with separate neighborhood typologies and year effects as well as paired year-neighborhood effects are presented in Tables 3-5 and 3-6, respectively. The findings from the first three categories (socio-demographics, cycling-specific built environment indicators, and trip characteristics) were consistent between the two binary logit models. The elasticities are presented in the far right column of Tables 3-5, 3-6, and 3-7. For continuous variables, the elasticities represent the percentage change in the probability of cycling if the value of the explanatory variable is increased by 10 percent. Whereas, for dummy variables, the elasticities represent the percentage change in the probability of cycling if the explanatory variable of interest is in effect.

Table 3-5 Results of binary logit model - separate neighborhood typologies and year effects

Category	Variable	Coefficient	Std. Error	P-Value	Elasticity*
socio-demographics	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	-0.7260	0.0746	0.000	-34.8%
	1 car per adult in HH	-1.5604	0.1002	0.000	-65.3%
	more than 1 car per adult in HH	-1.2030	0.2671	0.000	-53.8%
	single-person HH	0.1532	0.0851	0.072	7.6%
	non-single person HH				(reference)
	male	0.6346	0.0636	0.000	30.7%
	female				(reference)
	15 to 24 yrs old	0.8244	0.1685	0.000	39.0%
	25 to 34 yrs old	1.0013	0.1427	0.000	46.2%
	35 to 44 yrs old	1.1688	0.1415	0.000	52.6%
	45 to 54 yrs old	0.9407	0.1440	0.000	43.8%
	55 yrs old and older				(reference)
	full-time employee	-0.3268	0.1011	0.001	-16.2%
	part-time employee				(reference)
built environment	distance to cycling infrastructure (km)	-0.4885	0.0586	0.000	-37.1%
	intersection density	0.0097	0.0019	0.000	79.5%
	link to node ratio	1.6090	0.2039	0.000	381.7%
trip characteristics	commute trip distance squared	-0.0004	0.0001	0.001	-328.4%
	departed before 6:30 AM				(reference)
	departed between 6:31 and 7:30 AM	0.3193	0.1115	0.004	15.8%
	departed between 7:31 and 8:30 AM	0.6143	0.1070	0.000	29.8%
	departed between 8:31 and 9:30 AM	0.8142	0.1232	0.000	38.6%

	departed after 9:30 AM	0.6816	0.1134	0.000	32.8%
year	year 1998				(reference)
	year 2003	0.0775	0.1034	0.454	3.9%
	year 2008	0.3750	0.1012	0.000	18.5%
neighborhood type	downtown (1)	-1.3352	0.2867	0.000	-58.3%
	urban (2)	0.2651	0.0725	0.000	13.2%
	Urban-suburb(3)				(reference)
	Inner suburb (4)	-0.4374	0.0993	0.000	-21.5%
	Outer suburb (5)	-0.1286	0.1532	0.401	-6.4%
constant	constant	-8.9747	0.6307	0.000	-

Table 3-6 Results of binary logit model - paired neighborhood typologies and year effects

Category	Variable	Coefficient	Std. Error	P-Value	Elasticity
socio-demographics	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	-0.7259	0.0747	0.000	-34.77%
	1 car per adult in HH	-1.5610	0.1002	0.000	-65.29%
	more than 1 car per adult in HH	-1.2068	0.2671	0.000	-53.93%
	single-person HH	0.1515	0.0851	0.075	7.56%
	non-single person HH				(reference)
	male	0.6334	0.0637	0.000	30.63%
	female (reference)				(reference)
	15 to 24 yrs old	0.8228	0.1686	0.000	38.93%
	25 to 34 yrs old	1.0005	0.1427	0.000	46.19%
	35 to 44 yrs old	1.1679	0.1416	0.000	52.50%
	45 to 54 yrs old	0.9394	0.1440	0.000	43.76%
	55 yrs old and older				(reference)
	full-time employee	-0.3270	0.1011	0.001	-16.20%
	part-time employee				(reference)
built environment	distance to cycling infrastructure (km)	-0.4894	0.0587	0.000	-37.16%
	intersection density	0.0097	0.0019	0.000	79.50%
	link to node ratio	1.6018	0.2042	0.000	379.92%
trip characteristics	commute trip distance squared	-0.0003	0.0001	0.003	-247.14%
	departed before 6:30 AM				(reference)
	departed between 6:31 and 7:30 AM	0.3207	0.1116	0.004	15.89%
	departed between 7:31 and 8:30 AM	0.6153	0.1070	0.000	29.81%
	departed between 8:31 and 9:30 AM	0.8156	0.1232	0.000	38.63%
	departed after 9:30 AM	0.6823	0.1134	0.000	32.82%
1998	downtown (1) 1998	-0.8278	0.4335	0.056	-39.16%
	urban (2) 1998	0.3962	0.1399	0.005	19.54%
	urban-suburb (3) 1998				(reference)
	inner suburb (4) 1998	-0.3362	0.1873	0.073	-16.64%

	outer suburb (5) 1998	0.1657	0.2421	0.494	8.26%
2003	downtown (1) 2003	-1.2048	0.5260	0.022	-53.86%
	urban (2) 2003	0.4543	0.1523	0.003	22.32%
	urban-suburb (3) 2003	0.2546	0.1487	0.087	12.65%
	inner suburb (4) 2003	-0.3320	0.1963	0.091	-16.44%
	outer suburb (5) 2003	-0.1436	0.2917	0.622	-7.16%
2008	downtown (1) 2008	-1.2035	0.5269	0.022	-53.81%
	urban (2) 2008	0.7441	0.1482	0.000	35.61%
	urban-suburb (3) 2008	0.4995	0.1451	0.001	24.45%
	inner suburb (4) 2008	0.1153	0.1757	0.512	5.75%
	outer suburb (5) 2008	0.3271	0.2623	0.212	16.20%
constant	constant	-9.0752	0.6360	0.000	-

3.4.2.2. Socio-demographics

The first category of explanatory variables is socio-demographics, in which both household and individual-level characteristics were found to have statistically significant impacts on mode choice. For household-level characteristics, we found that individuals that live in a household with private vehicles have a decreased likelihood of cycling to work than those living in a household with no cars. In fact, individuals who live in a household with cars are less likely to cycle by 35 to 65 percent than individuals who have access to cars in their households. In our binary logit models, it was found that having zero to one car per adult, exactly one car per adult, and more than one car per adult have coefficients of -0.73, -1.6, and -1.2 while holding absence of cars as the reference case. This is a similar finding to a study by Cervero and Duncan (2003) that has found that the number of vehicles in the household is negatively associated with cycling, as the coefficient of this variable was -0.7. In a study of non-motorized commuting in US by Plaut (2005), it was found that individuals living in a household with no cars was positively associated with the probability of cycle to work (coefficients 1.0 to 3.1), while owning two or more cars had the opposite effect. Instead of looking at the influence of auto ownership, Heinen et al. (2013) explored the effects of auto availability for commuting. They found that 'always' having a car available for commuting decreased the probability of being a commuter cyclist, while 'sometimes' having a car available for commuting had the opposite influence. In our study, living in a single-person household was found to be positively associated with the likelihood of cycling, with increases of up to 8 percent. It is important to note that usually with increasing household size, complexity of the relationship between mode choice and household size also increases especially when children are involved.

In terms of individual-level socio-demographics, we found that gender, age and employment status influenced cycling levels. Similar to findings of Heinen et al. (2013), Plaut (2005), and Cervero and Duncan (2005), the likelihood of cycling was positively associated with being male, as males are more likely to cycle to work by 31 percent than females. In our models, the coefficient of the dummy variable which represents the sex of the individual (1 = male, 0 = female) was 0.6. Employment status influenced cycling levels as full-time employees were less likely to cycle than part-time employees by 16 percent. The coefficient of the dummy variable which represents the employment status of the individual (1 = full-time, 0 = part-time) was -0.3. It was found that the highest elasticities were attributed to individuals' age, where the probability of cycling to work doubles if individuals are between ages of 35 and 44 compared to the probability if the individuals are 55 years of age or older. In general, individuals between the ages 25 and 54 years were found to cycle significantly more relative to young adults and seniors. In our study, we found that youth and younger adults (15 to 34 years old) actually cycle less compared to mid-aged adults (ages 35 to 44). While holding seniors (ages 55 and up) as reference case, the coefficients estimated from our models were 0.8, 1.0, 1.2, and 0.9 for age categories of 15 to 24, 25 to 34, 35 to 44, and 45 to 54 years. This is a different finding from other studies, as most studies find that being young is positively associated with cycling. In Heinen et al. (2013), being less than 30 years of age was found to have the largest coefficient followed by the age group 30 to 45 years and 45 to 60 years of age. While, in a study by Titze et al. (2008), the age groups 21 to 30 years had the largest coefficient, followed by age group 41 to 50 years old. In our study region, we find that cycling levels peak at the age group 35 to 44 years. It would be interesting to conduct stated preference surveys to find explanations to why mid-aged adults choose to cycle more than young adults who are in optimal physical conditions.

3.4.2.3. Cycling-specific built environment indicators

The second category of variables was cycling-specific built environment indicators. As expected, an increase in the distance to nearest cycling facilities from residence reduces the probability of individuals choosing to cycle to work. The coefficient of this variable was around -0.5. Based on the elasticities, a 10 percent increase in distance to nearest cycling facilities (measured in km) would on average result in a 37 percent reduction in the probability of choosing to cycle. Similarly, Cervero and Duncan (2003) found that increased pedestrian-/bike-friendly design factor at the origin increased the likelihood to achieve a trip by bicycle (with a coefficient of 0.23). On the other hand, Dill and Voros (2006) found that objectives measures of proximity to off-street trails and bike lanes was not associated with higher levels of cycling. The influence of cycling facilities can be further investigated as the decision to cycle to work is also influenced by the cycling facilities in close proximity to the path from home to work, rather than the cycling facilities near their residence alone. For example, the "downtown" neighborhood type has the highest cycling network densities (almost double the second highest cycling network density neighborhood type), yet, has below average cycling levels (1.5 percent modal share in 2008). Further investigation would be necessary in order to clarify the relationship between the proximity to cycling facilities and mode choice. Perhaps, the inclusion of indicators that represent the proximity to cycling facilities along the path of the home-based work trip and/or the destination (workplace) can shed further light on the influence of cycling facilities. Furthermore, intersection density and link to node ratio of residential location were found to be positively associated with the choice of cycling to work (coefficients of 0.01 and 1.6), suggesting that street design with higher connectivity improves cycling levels. Similar findings have been made by Cervero et al. (2009) as medium to high street densities were associated with more cycling. Nonetheless, the same suggestion can be made for the street design variables in terms of exploring the indicators along the path of the trip as well as the destination.

3.4.2.3. Trip characteristics

The third category of variables was trip characteristics, which includes commute distance and departure times. Similar to previous literature (Heinen et al. 2013), the negative coefficients of -0.0003 to -0.0004 for the commute distance variable indicates that greater distances between residential location and work-related destination result in decreased likelihood to cycle to work. In many other studies, the trip distance was found to be negatively associated with cycling with coefficients ranging from -0.1 to -0.29 (Heinen et al. 2013; Cervero and Duncan, 2003). Furthermore, the likelihood to cycle to work was found to be positively associated with increased probabilities of cycling by 39 percent for trips that departed during peak hours from 8:31 to 9:30 AM (which has a coefficient of 0.8). Generally, there is a strong positive association between individuals' likelihood to cycle and departure times after 7:30 AM. The coefficients of dummy variables representing departure after 7:30 AM range between 0.6 to 0.8, when holding departures before 6:30 AM as reference. These results imply that commuters are more likely to cycle during peak AM hours when congestion is at its worst. The results of the study of cycling in Dublin by Caulfield (2014) have demonstrated that individuals living in areas that have experienced an increase in cycling have later departure times than those living in areas with no change in cycling levels.

3.4.2.4. Evolution of cycling and effects of neighborhood typologies

The main objective of this study is to explore the effects of neighborhood typologies on cycling as well as the evolution of cycling. Thus, we are interested in comparing the results of the different models to find consistencies and/or variations in the effect sizes of neighborhood typologies on cycling. The built environment indicators included in the generation of neighborhood typologies were population and employment densities, land use mix, public transit accessibility, and bicycle lane densities. In literature, population and employment densities have been found to be positively associated with cycling levels (Parkin, 2008; Winters et al. 2010; Pinjari et al. 2007). Thus, we expect individuals living in neighborhood typologies with high population and employment densities, including downtown (1), urban (2), and to some extent urban-suburb (3) to have increased probability of cycling. Land use mix at the origin of the trip has been found to be positively associated with cycling levels (Cervero and Duncan, 2003; Winters et al. 2010; Pinjari et al. 2011). Therefore, we expect individuals living in central neighborhood typologies with relatively land use mix (entropy index values ranging from 0.48 to 0.63) to cycle more. High bicycle lane densities have been found to increase cycling levels

(Pinjari et al. 2011). As a result, we expect individuals living in neighborhood typologies with higher cycling network densities to have higher probabilities to cycle to work.

Starting with the results of the simple binary logit model (Table 3-5), we see that the likelihood of cycling has increased with time. Relative to 1998, the likelihood to cycle to work increased for individuals living in 2003 and 2008 by 4 and 19 percent, respectively. The coefficients from the model are 0.08 and 0.38 for 2003 and 2008, respectively. As mentioned briefly in the introduction, the Island of Montreal has not experienced much change in its built environment during the study period. Furthermore, in all of our models, we have controlled for a few yet critical cycling-specific built environment indicators. Therefore, the relatively high elasticities of year variables can only be explained by the following: (i) changes in the built environment during the study period that were not captured in the models but increased the likelihood to cycle; and (ii) change in the population's attitude towards cycling. Many studies on behavioral aspects of cycling have found a phenomenon of a positive feedback cycle which prevails in many large cities (Robinson, 2005; Jacobsen, 2003). Essentially, it has been found that promotional efforts for cycling (such as improvement of cycling facilities) increase cycling levels as well as safety. The new, increased levels of cycling and safety further attract cyclists, increasing safety and cycling activity to an even greater extent. The promotion of active transportation, especially cycling has been a key mandate for many municipalities in Montreal. Perhaps, the significant increase in cycling that we have witnessed even after controlling for socio-demographics, trip characteristics and the built environment, can be partially explained by this phenomenon. In terms of the effects of residential location, we found that living in urban (2) has the greatest positive influence on the likelihood to cycle to work. Urban (2) has a coefficient of 0.26, and an elasticity of 13 percent. This indicates that living in urban (2) instead of urban-suburb (3) increases the likelihood of an individual to cycle to work by 13 percent. The urban-suburb has the second most positive influence on cycling. The other neighborhood typologies including downtown (1), inner suburb (4), and outer suburb (5) have negative influence on an individual's likelihood to cycle to work relative to that if the individual lived in urban-suburb (3). The coefficients of downtown (1), inner suburb (4), and outer suburb (5) are -1.34, -0.44 and -0.13, respectively. As mentioned earlier, population and employment densities, land use mix and public transit accessibility have found to be positively associated with cycling. When compared to urban-suburb (3) (reference neighborhood typology), downtown (1) has much higher values for the built environment indicators included in the neighborhood typologies that we have generated. The same is true for inner suburb (4) when compared to outer suburb (5). Nonetheless, we observed that the coefficients of downtown (1) is -1.3 with an elasticity of -58 percent. In the paragraph below, a set of possible explanations for this observation is presented.

The above findings of the growth of cycling over time are confirmed by the overall trend of the results found in the second binary logit model (Table 3-6). This model aims to capture the cross effects of neighborhood typologies and time period on utilitarian cycling. The reference case is urban-suburb (3) neighborhood typology for year 1998. The elasticities of the variables representing the cross effects can be used to determine the evolution of neighborhood effects on cycling for each of the neighborhood typologies. With the exception of downtown (1), all of the effects of neighborhood typologies have grown positively over time. The greatest growth was found for urban (2) neighborhoods. Individuals living in this neighborhood typology have increased likelihood to cycle to work by 20, 22, and 36 percent in 1998, 2003 and 2008 with respect to the likelihood if these individuals resided in urban-suburb (3) neighborhoods in 1998.

A similar trend was found for the effects of urban-suburb (3), where the probability to cycle to work has increased by 13 and 24 percent relative to 1998 levels. Inner suburb (4) and outer suburb (5) have experienced the similar trend, as the elasticities have increased from -17 to 6 percent and 8 to 16 percent between 1998 and 2008. The evolution of the neighborhood effects of downtown (1) appears as an anomaly as the elasticities have decreased from -39 to -54 percent relative to the effects of urban-suburb (3) in 1998. This model allowed us to further breakdown the effect of time into neighborhood typology-levels. Downtown (1), which is characterized as the neighborhood with the highest densities and accessibilities, most diverse mix of land use and greatest cycling networks, has been experiencing declines in neighborhood effects. This is surprising as the little improvement in regional built environment over the study period occurred most strikingly in downtown (1). There are a few potential sources of explanations for this observed trend. First, it is important to note that downtown (1) has experienced a significant growth in walking modal share during the same period. Second, most built environment improvements in respect to density, diversity and design, improve both cycling and walking mode share. Third, average home-based work trips for downtown (1) residents are significantly shorter than those of residents residing in other neighborhoods. These three pieces of evidence can work together to suggest that for many downtown (1) residents, walking may have become an increasingly more convenient option.

3.4.3. Simultaneous equation model

The results of the Simultaneous Equation Model are presented in Tables 3-7 and 3-8. The model which represents the choice of neighborhood typology of residence is presented in Table 3-7. Whereas, the model which represents mode choice (cycle or not) is presented in Table 3-8.

3.4.3.1. Neighborhood typology choice model of SEM

In this section, we are interested in the choice of residential neighborhood typologies, which is modelled as a function of the individuals' household-level socio-demographic characteristics. The results of this model (Table 3-7) provide insight into the effects of household-level characteristics such as auto ownership, household size, employment status as well as number of children on residential neighborhood choice. Table 3-7 presents the results of this model as well as the respective elasticities. Urban-suburb (3) was designated as the reference group. Household auto ownership was associated the most negatively with the choice of living in downtown (1), followed by urban (2). On the other hand, the choice of living in the suburbs (4 and 5) was positively influenced with high auto ownership. Single-person households have increased likelihood of living in downtown and urban (1 and 2), while non-single person households have increased the likelihood of living in the suburbs (4 and 5). With increasing number of employed household members, the likelihood of choosing to live in central neighborhoods decreased. This can be explained by the higher proportion of single-person households and university students in urban areas. Households with more retirees have greater likelihood to live in suburbs.

Table 3-7 Results of neighborhood typology choice of SEM

Neighborhood Typologies	Variable	Coefficient	Std. Error	P-Value	Elasticity
downtown (1)	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	-0.7442	0.0813	0.000	-41.5%
	1 car per adult in HH	-0.9400	0.0815	0.000	-58.8%
	more than 1 car per adult in HH	-1.4353	0.3150	0.000	-75.8%
	single-person HH	0.3497	0.0910	0.000	16.2%
	non-single person HH				(reference)
	no. of persons under 5 yrs old in HH	-0.3152	0.0985	0.001	-18.8%
	no. of full-time employees in HH	-0.2143	0.0608	0.000	-50.7%
	no. of part-time employees in HH	-0.3498	0.0978	0.000	-24.9%
	no. of retirees in HH	-0.7652	0.1425	0.000	-40.0%
	constant	-2.3540	0.1204	0.000	-
urban (2)	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	-0.3860	0.0356	0.000	-25.7%
	1 car per adult in HH	-0.7419	0.0368	0.000	-51.9%
	more than 1 car per adult in HH	-0.8452	0.1035	0.000	-60.2%
	single-person HH	0.2042	0.0421	0.000	9.0%
	non-single person HH				(reference)
	no. of persons under 5 yrs old in HH	-0.0260	0.0327	0.426	-0.7%
	no. of full-time employees in HH	-0.0222	0.0225	0.323	-10.4%
	no. of part-time employees in HH	-0.0020	0.0361	0.956	-2.4%
	no. of retirees in HH	-0.2846	0.0415	0.000	-12.8%
	constant	-0.3079	0.0496	0.000	-
inner suburb (4)	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	0.8474	0.0398	0.000	34.0%
	1 car per adult in HH	1.3101	0.0397	0.000	42.2%
	more than 1 car per adult in HH	1.4855	0.0835	0.000	43.7%
	single-person HH	-0.4027	0.0424	0.000	-21.0%
	non-single person HH				(reference)
	no. of persons under 5 yrs old in HH	-0.0090	0.0291	0.756	0.4%
	no. of full-time employees in HH	0.2126	0.0198	0.000	39.1%
	no. of part-time employees in HH	0.2245	0.0328	0.000	12.4%
	no. of retirees in HH	0.1439	0.0343	0.000	12.7%
	constant	-1.5642	0.0503	0.000	-
outer suburb (5)	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	1.6614	0.0856	0.000	64.2%
	1 car per adult in HH	2.9169	0.0853	0.000	84.9%
	more than 1 car per adult in HH	3.2832	0.1174	0.000	87.8%
	single-person HH	-1.4013	0.0672	0.000	-61.2%
	non-single person HH				(reference)
	no. of persons under 5 yrs old in HH	0.1026	0.0355	0.004	7.5%

	no. of full-time employees in HH	0.2479	0.0258	0.000	46.5%
	no. of part-time employees in HH	0.3295	0.0429	0.000	19.2%
	no. of retirees in HH	0.2911	0.0439	0.000	21.4%
	constant	-3.8444	0.0945	0.000	-

3.4.3.2. Mode choice model of SEM

In the SEM, residential choice is modelled simultaneously with mode choice, where mode choice is determined by many factors including socio-demographics, cycling-specific built environment indicators, trip characteristics, and chosen neighborhood typology. Table 3-8 presents the results of the mode choice model of SEM.

Table 3-8 Results of mode choice of SEM

Category	Variable	Coefficient	Std. Error	P-Value	Elasticity
socio-demographics	0 car per adult in HH				(reference)
	0 to 1 car per adult in HH	-0.7520	0.0730	0.000	-35.9%
	1 car per adult in HH	-1.5228	0.1067	0.000	-64.2%
	more than 1 car per adult in HH	-1.1561	0.2708	0.000	-52.1%
	male	0.6370	0.0639	0.000	30.8%
	female				(reference)
	15 to 24 yrs old	0.7980	0.1682	0.000	37.9%
	25 to 34 yrs old	0.9861	0.1426	0.000	45.6%
	35 to 44 yrs old	1.1586	0.1416	0.000	52.2%
	45 to 54 yrs old	0.9327	0.1442	0.000	43.5%
	55 yrs old and older				(reference)
	full-time employee	-0.3305	0.1015	0.001	-16.4%
	part-time employee				(reference)
built environment	distance to cycling infrastructure (km)	-0.4929	0.0587	0.000	-37.4%
	intersection density	0.0098	0.0019	0.000	80.3%
	link to node ratio	1.6210	0.2044	0.000	384.5%
trip characteristics	commute trip distance squared	-0.0004	0.0001	0.001	-328.4%
	departed before 6:30 AM				(reference)
	departed between 6:31 and 7:30 AM	0.3216	0.1117	0.004	15.9%
	departed between 7:31 and 8:30 AM	0.6182	0.1073	0.000	29.9%
	departed between 8:31 and 9:30 AM	0.8212	0.1236	0.000	38.9%
	departed after 9:30 AM	0.6829	0.1137	0.000	32.9%
year	year 1998				(reference)

	year 2003	0.0782	0.1035	0.450	3.9%
	year 2008	0.3746	0.1013	0.000	18.5%
neighborhood type	downtown (1)	-1.3135	0.3117	0.000	-57.6%
	urban (2)	0.4819	0.1489	0.001	23.6%
	Urban-suburb(3)				(reference)
	Inner suburb (4)	-0.4062	0.1667	0.015	-20.0%
	Outer suburb (5)	-0.2133	0.1742	0.221	-10.6%
constant	constant	-9.0553	0.6398	0.000	-

3.4.3.2.1. Socio-demographics

In Table 3-8, the first category of explanatory variables is socio-demographics, in which both household and individual-level characteristics were found to have similar influences on mode choice as those of binary logit models. For household-level characteristics, that living in a household with private vehicles is associated with decreased likelihood to cycle to work. In the SEM, it was found that having zero to one car per adult, exactly one car per adult, and more than one car per adult have coefficients of -0.75, -1.52, and -1.16 while holding absence of cars as the reference case.In fact, individuals who live in a household with cars are less likely to cycle by 35 to 52 percent than individuals who have access to cars in their households. Unlike the binary logit models, the dummy variables representing household size (single or multi-person household) were found to be insignificant, thus, excluded in the SEM. In terms of individual-level socio-demographics, similar influences were found in SEM versus binary logit models. Gender, employment status and age were found to have the exact same influence on cycling as it did in the previous models. Being male increased the likelihood to cycling by 31 percent (coefficient of 0.64) and being employed full-time instead of part-time decreased the likelihood to cycle by 16 percent (coefficient of -0.33). Once again, the highest elasticities were attributed to individuals' age, where the likelihood of cycling to work more than doubles if individuals are between ages of 35 and 44 relative to if the individuals are 55 years of age or older. While holding seniors (ages 55 and up) as reference case, the coefficients estimated from our models were 0.8, 1.0, 1.2, and 0.9 for age categories of 15 to 24, 25 to 34, 35 to 44, and 45 to 54 years. We observe the same trend as earlier, in which individuals between the ages 25 and 54 years were found to cycle significantly more relative to young adults and seniors.

3.4.3.2.2. Cycling-specific built environment indicators

The second category of variables was cycling-specific built environment indicators (Table 3-8). The results are very consistent with those of binary logit models. The variable representing distance to the nearest cycling infrastructure had a coefficient of -0.49. Upon caclulations of the elasticity, it was found that a 10 percent increase of this variable would reduce the probability of choosing to cycle to work by 37 percent. Furthermore, intersection density and link to node ratio of residential location had positive coefficients of 0.01 and 1.6.A 10 percent increase in intersection density and link to node ratio of residential location would increase the likelihood to bicycle to work by 80 and 385 percent. Once again, these results confirm that street design and street connectivity are positively associated with cycling levels.

3.4.3.2.3. Trip characteristics

The third category of variables was trip characteristics, which includes commute distance and departure times (Table 3-8). Airline commute distance was found to be negatively associated with utilitarian cycling with a coefficient of -0.0004. Furthermore, the likelihood to cycle to work increased by 39 percent for departure times between 8:31 and 9:30 AM. The coefficients of dummy variables representing departure after 7:30 AM range between 0.6 to 0.8, when holding departures before 6:30 AM as reference. Once again, we find a strong positive association between individuals' likelihood to cycle and departure times after 7:30 AM.

3.4.3.2.4. Evolution of cycling and effects of neighborhood typologies

The key findings of the effects of the neighborhood endogenous variables of SEM are explained below. For this model, the urban-suburb (3) neighborhood typology was held as the reference case. First, we found that choosing to live in downtown (1) causes the greatest decrease in the likelihood of cycling to work compared to other neighborhoods. In fact, living in downtown (1), inner suburb (4), and outer suburb (5) in comparison to living in urban-suburb (3) decreases the likelihood to cycle to work by 58, 20, and 11 percent, respectively. These results are similar to those of the first binary logit model, which looked at neighborhood typologies and year effects separately while not controlling for residential self-selection. In the binary logit model, we saw that living in downtown (1), inner suburb (4), and outer suburb (5) in comparison to living in urban-suburb (3) decreases the likelihood to cycle to work by 58, 22, and 6 percent, respectively. Furthermore, the binary logit model estimated that living in urban (2) versus urban-suburb (3) increased the likelihood of cycling by 13 percent. However, upon controlling for residential self-selection in the SEM, we observed that this effect is almost twice as large at 24 percent. This implies that built environment of urban (2) neighborhoods encourages cycling to a greater degree than the observed difference between the two neighborhoods, urban (2) and urban-suburb (3). Finally, we observed that the likelihood to cycle increased with time. Similar to the binary logit model, the SEM results indicate that an individual is more likely to cycle in 2003 and 2008 than 1998 by 4 and 19 percent.

3.4.4. Propensity score matching

Propensity score matching involves four main steps: (i) estimate a model to predict propensity score of choosing to live in the treatment neighborhood typology; (ii) match individuals from treatment/control groups based on propensity scores; (iii) check balance of explanatory variables; and (iv) calculate average treatment effects. The results from each of the steps are explained in this section.

3.4.4.1. Estimating propensity scores

The first step of propensity score matching (PSM) was to estimate a binary logit model explaining household location choice for each neighborhood pair. For illustration purposes, we presented the binary logit model for Pair G for each of the years (1998, 2003, and 2008) in Table 3- 9. The treatment group for this pair is urban (2) and control group is outer suburb (5). Thus, the models are explaining the likelihood of living in urban (2) versus outer suburb (5) given the household-level socio-demographics. We found that number of private vehicles per adult in the household was negatively associated with choosing to live in urban (2). Also, we found that as the female-to-male ratio grows in the household, the propensity to live in urban (2) decreased. Finally, the number of toddlers and students in the household was found to be negatively associated with choosing to live in urban (2) neighborhoods. Using this model, we estimated the propensity score of choosing to live in urban (2) versus outer suburb (5).

Table 3-9 Binary logit models for choice of living in urban (2) vs. outer suburb (5) of PSM

Variable	1998		2003		2008	
	coefficient	p-value	coefficient	p-value	coefficient	p-value
no. of cars per adult in HH	-2.2555	0.000	-2.2951	0.000	-2.0149	0.000
female to male ratio for HH	-0.1664	0.120	-0.1998	0.070	-0.2406	0.034
no. of persons under 5 yrs old in HH	-0.2984	0.000	-0.3713	0.000	-0.0229	0.761
no. of students in HH	-0.4368	0.000	-0.4539	0.000	-0.3922	0.000
constant	2.7885	0.000	2.7835	0.000	2.4620	0.000

no. of observations	7119	6792	6242
McFadden R-square	0.135	0.146	0.125

3.4.4.2. Matching individuals based on propensity scores

Based on the propensity scores estimated in the previous step, we performed a matching process, which allowed us to find an "identical" person from those living in urban (2) to match each person living in outer suburb (5). Upon performing "PSMATCH2" in STATA, 14 observations were dropped for Pair G.

3.4.4.3. Checking post-PSM balance of explanatory variables

The third step of PSM was to determine whether or not the matched individuals from treatment and control groups were systematically different. Table 3-10 demonstrates the standard differences of explanatory variables prior to and after the PSM process. The standard differences of 10 and lower are generally accepted. From the table below, we observed that the standard differences prior to matching range from 7 to 87 percent in absolute terms. However, after matching, we observed that the standard differences were well below the cut off value of 10 percent.

Table 3-10 Standard differences of observed covariates for 1998 of PSM

Variable	Unmatched mean			Matched mean		
	Urban (2)	Outer suburb (5)	Std. diff. %	Urban (2)	Outer suburb (5)	Std. diff. %
no. of cars per adult in HH	0.478	0.811	-87.4	0.473	0.478	-1.3
female to male ratio for HH	0.474	0.494	-7.7	0.474	0.470	1.6
no. of persons under 5 yrs old in HH	0.132	0.206	-16.1	0.132	0.128	0.8
no. of students in HH	0.507	0.872	-38.7	0.507	0.486	2.2

3.4.4.4. Calculation of average treatment effects

The ultimate goal of propensity score matching (PSM) is to estimate the "true" impact of the neighborhood typologies on cycling. The observed differences between cycling levels between two neighborhood typologies is referred to as the observed influence. In other words, the observed influence of residential location on cycling levels is the difference in mean cycling levels between pre-PSM treatment and control groups. In our study, the observed difference is the sum of residential self-selection effect and average treatment effect (ATE). The ATE represents the average change in cycling behavior when a randomly selected person is moved from the control group to the treatment group. Similar to Cao et al. (2010), the ATE is computed as the difference between mean cycling levels between the matched treatment and control groups. In our example of Pair G, the ATE is calculated as mean cycling levels of chosen individuals living in urban (2) minus that of the chosen individuals living in outer suburb (5). The ATE of each of the pairs is presented in Table 3-11. The neighborhood typologies have been paired in such a way that treatment represents more central neighborhoods compared to the control. For illustration purposes, once again we refer to Pair G, where treatment is urban (2) and control group is outer suburb (5). For this pair, we expect positive ATE values as the built environment of urban (2) neighborhoods are significantly more cycle-friendly. In fact, urban (2) is characterized by relatively high employment and population densities with great public transit accessibility. Furthermore, urban (2) has a great deal of cycling facilities and cycle-friendly street design and connectivity. The ATE values of Pair G are 0.0145, 0.0242, and 0.0416 for 1998, 2003, and 2008, respectively. This means that in 1998, if a randomly selected individual is moved from outer suburb (5) to urban (2), the likelihood of that individual cycling to work increases by 1.45 percent. We observed that in the case of Pair G, the ATE values grow positively over time. This indicates that even after taking residential self-selection into account, living in urban (2) is having an increasingly positive effect on utilitarian cycling. This trend can be explained by the reasoning that the improvement in built environment and/or pro-cycling attitudinal changes in urban (2) is occurring at a faster rate than that of outer suburb (5).

The key findings of the evolution of the true impact of neighborhood typologies on cycling from PSM are explained. In 1998, we observe a trend of positive ATE. Meaning, after taking residential self-selection in to account, living in more central neighborhoods increases individuals' likelihood of cycling. In 2003 and 2008, we observe a similar trend for all neighborhood typologies with the exception of downtown (1). We see that living in downtown negatively influences cycling activity when compared to other neighborhoods. It is important to note that the negative influence of living in downtown (1) on cycling activity grows over time. This reinforces our previous findings from the binary logit model with cross neighborhood and year effects. The most significant trend found through the PSM is the positive growth of the ATE of urban (2) and suburban (3) neighborhoods over the study period.

Table 3-11 Average treatment effects (ATE) of neighborhood typologies on cycling

Pair	Treatment	Control	ATE		
			1998	2003	2008
A	downtown (1)	urban (2)	0.03197	-0.04075	-0.0535
B	downtown (1)	urban-suburb (3)	0.03644	-0.02289	-0.0311
C	downtown (1)	inner suburb (4)	0.02088	-0.00628	-0.0108
D	downtown (1)	outer suburb (5)	-0.00096	0.01345	-0.0267
E	urban (2)	urban-suburb (3)	0.02259	0.00297	0.0054
F	urban (2)	inner suburb (4)	0.01731	0.0195	0.0215
G	urban (2)	outer suburb (5)	0.0145	0.0242	0.0416
H	urban-suburb (3)	inner suburb (4)	0.02449	0.00524	0.0170
I	urban-suburb (3)	outer suburb (5)	0.00603	0.00503	0.0190
J	inner suburb (4)	outer suburb (5)	0.00385	0.00361	0.0070

3.5. Conclusion

This research here has presented some empirical evidence on the effects of the built environment, as described through neighborhood types on cycling over time. For this study, a large sample of commuters who reside on the Island of Montreal were used in order to evaluate trends in utilitarian cycling. One of the key findings is the general increase in the likelihood to cycle over time in the study region. In fact, neighborhood effects of all neighborhood types with the exception of downtown (1) have grown increasingly positive over time. Specifically, urban areas (2 and 3) have been experiencing the greatest growth. On the other hand, living in downtown (1) has influenced cycling levels in an increasingly negative trend. The built environment of the study region has not evolved significantly during the 10-year study period. As a result, we conclude that the observed change in cycling activity is explained by attitudinal and cultural changes in the population over time. Determining the reasons behind the attitudinal change in cycling was not the focus of this study – the available data does not allow us to explain these changes. Promotional efforts by local municipalities and agencies – such as improving safety, campaigns, etc. have positively influenced cycling activity.

One of the limitations of our research is the fact that preferences survey data was not included – this is not collected in traditional O-D surveys. Also, only three waves of data over time were used. In few studies regarding household location choice and mode choice, both observed and stated preferences. As preference survey data was not available, our models were not able to control for individuals' attitudes toward residential location and cycling. As a result, the effects of neighborhood typologies represent not only the effects of the built environment but also attitudes. This study only controls for socio-demographics and built environment on one travel behavior outcome, cycling. However, both active and public transportation activity levels merit exploration in order to obtain more insight into sustainable commuter behavior. Finally, it would have been ideal to control for physical environment characteristics such as weather and elevation changes. However, due to data restrictions, this was not possible our analysis.

4. Concluding Remarks

The objective of this thesis was to explore the relationship between the built environment and travel behavior outcomes with respect to time. In the first section, we use CO_2 emissions produced by passenger transport to forecast future emissions under different built environment scenarios. Regional emissions models are developed for this purpose. Also, emissions data was obtained from a previous study by Zahabi et al. 2013. In the second section, we explored the effects of neighborhood typologies on cycling over the same period. The major findings of this research are summarized below.

In Chapter 2, we first developed region-specific models to estimate average household CO_2 as a function of BE and SE characteristics for years 1998, 2003, and 2008. From the results of these aggregate models, we found that households that are surrounded by more accessible, dense built environments and are of closer distance to CBD produce significantly lower average CO_2 emissions, than those with poor BE – These findings are in accordance with the recent work of Zahabi et. Al. 2013 using the same data but a disaggregate approach in the same region. As observed by Zahabi using disaggregate models, we also found that emissions were consistently decreasing from the beginning of the study period to the end. In fact, estimated average household CO_2 emissions were 11.40, 10.00, and 9.06 kg/day for 1998, 2003, and 2008, respectively. The advantage of aggregate models with respect to desegregate models is that the evaluation of scenarios and projections can be relatively simple. . It is important to note that during the same period, the region experienced 12.5 percent growth in its population size. From these results, we have found that average household emissions are decreasing at a faster rate than population growth (-2.1 versus 1.2 percent), which resulted in an annual decrease of 1 percent for the total CO_2 emissions for the region. The decrease in average and total emissions can be explained by several factors including attitudinal changes in the population, increased use of active and public transportation as well as the introduction of increasingly fuel-efficient and/or electric vehicles.

As a main objective in this Chapter 2, we forecasted future average household CO_2 emissions for three scenarios – business as usual (BAU), and in accordance to PMAD policies and MTQ population forecasts. PMAD is a regional sustainable development plan for 2031, which focuses on integrated planning of land use and transportation as well as efficient allocation of growing population. The forecasted average household CO_2 emissions are significantly lower for the PMAD scenario in comparison to the MTQ and BAU scenarios with 5.5, 5.85, and 6.13 kg/day, respectively. The average household and total of region's CO_2 emissions were forecasted to be lower in PMAD versus the BAU scenario by 10.3 and 10.4 percent. From these results, we can conclude that sustainable development policies including improvements in the built environment and efficient population allocation are effective approaches to stabilize and or reduce net transport-related CO_2 emissions.

In Chapter 3, we adopted three methodological approaches to examine the effects of neighborhood typologies on cycling over time; (i) simple binary logit model; (ii) simultaneous equation model; and (iii) propensity score matching model. The results of the models together provided great insight into the evolution of the effects of neighborhood typologies in Montreal. We observed that the effects of all neighborhood typologies on utilitarian cycling, with the exception of downtown (1) have grown increasingly positive over time. Specifically, urban areas (2 and 3) have been experiencing the greatest growth. Meanwhile, living in downtown (1) has influenced cycling levels in an increasingly negative trend. In the duration of the study period, the built environment of Montreal has changed very little. As a result, we conclude that the observed change in cycling activity is explained by attitudinal changes in the population over time.

The travel behavior trends that we have found in the two studies demonstrate that the externalities from passenger transport are decreasing while the mode share of sustainable transport is increasing. There is a clear relationship between the two findings can be explained by modal shift away from motorized travel and towards active and public transportation. Furthermore, we can attribute the observed trends to change in attitudes of the population as well as regional strategic plans to promote sustainable transport.

Appendix A

Table A-1 Summary statistics of SE and BE indicators at census tract level for Island of Montreal (Region 1)

Category	Variable	Mean 1998	Std. Dev 1998	Mean 2003	Std. Dev 2003	Mean 2008	Std. Dev 2008
DV	ln of average household CO_2	1.98	0.53	1.80	0.48	1.53	0.59
SD	No. of full-time workers in HH	0.54	0.18	0.61	0.16	0.58	0.14
	No. of part-time workers in HH	0.53	0.12	0.54	0.11	0.55	0.11
	No. of persons under 15 years of age in HH	0.37	0.17	0.35	0.17	0.34	0.16
	No. of persons between 25 and 64 years of age in HH	1.29	0.21	1.26	0.24	1.28	0.23
	No. of persons 65 years of age and over in HH	0.30	0.12	0.30	0.13	0.30	0.14
	Average Household Income (1000s of CAD$)	40.96	22.65	45.53	25.91	48.13	33.20
	Household density (1000s/km^2)	4.04	3.97	4.22	4.15	4.31	4.29
	Intersection density (km^2)	84.51	52.31	85.04	54.29	85.04	54.28
	Travel Time to CBD (minutes)	25.10	14.16	25.10	14.16	25.10	14.16
BE	Job accessibility (30 minutes) (1000s)	787.35	310.68	858.85	337.89	900.72	352.03
	Entropy index	0.56	0.15	0.56	0.15	0.56	0.15
	Public transit accessibility	217.70	140.45	218.38	141.71	218.38	141.71
	Public transit modal share	0.33	0.11	0.34	0.11	0.34	0.11

*DV = dependent variable; SD = socio-demographics; BE = built environment

Table A-2 Summary statistics of SE and BE indicators at census tract level for Laval (Region 2)

Category	Variable	Mean 1998	Std. Dev 1998	Mean 2003	Std. Dev 2003	Mean 2008	Std. Dev 2008
DV	ln of average household CO_2	2.57	0.28	2.47	0.30	2.26	0.40
SD	No. of full-time workers in HH	0.75	0.17	0.81	0.20	0.76	0.18
	No. of part-time workers in HH	0.62	0.12	0.58	0.10	0.59	0.10
	No. of persons under 15 years of age in HH	0.52	0.18	0.48	0.17	0.44	0.15
	No. of persons between 25 and 64 years of age in HH	1.52	0.23	1.45	0.24	1.41	0.23
	No. of persons 65 years of age and over in HH	0.28	0.13	0.33	0.14	0.37	0.14
	Average Household Income (1000s of CAD$)	49.13	12.22	55.63	34.42	55.82	24.84
	Household density (1000s/km^2)	1.90	1.51	2.01	1.59	2.15	1.71
	Intersection density (km^2)	46.47	26.65	46.47	26.65	46.47	26.65
	Travel Time to CBD (minutes)	54.43	8.83	54.43	8.83	54.43	8.83
BE	Job accessibility (30 minutes) (1000s)	272.34	113.17	305.28	124.95	335.92	126.70
	Entropy index	0.41	0.17	0.41	0.17	0.41	0.17
	Public transit accessibility	27.79	30.18	28.05	30.67	30.44	36.39
	Public transit modal share	0.12	0.05	0.13	0.05	0.14	0.05

Table A-3 Summary statistics of SE and BE indicators at census tract level for North Shore (Region 3)

Category	Variable	Mean 1998	Std. Dev 1998	Mean 2003	Std. Dev 2003	Mean 2008	Std. Dev 2008
DV	ln of average household CO_2	2.92	0.22	2.81	0.35	2.65	0.38
SD	No. of full-time workers in HH	0.75	0.18	0.81	0.19	0.79	0.17
	No. of part-time workers in HH	0.65	0.10	0.62	0.10	0.62	0.10
	No. of persons under 15 years of age in HH	0.63	0.19	0.56	0.17	0.47	0.15
	No. of persons between 25 and 64 years of age in HH	1.56	0.21	1.51	0.22	1.45	0.22
	No. of persons 65 years of age and over in HH	0.20	0.09	0.23	0.09	0.27	0.11
	Average Household Income (1000s of CAD$)	47.77	12.16	51.32	13.93	54.12	14.23
	Household density (1000s/km^2)	1.62	1.75	1.79	1.96	2.08	2.42
	Intersection density (km^2)	46.97	40.51	71.14	83.27	71.14	83.27
	Travel Time to CBD (minutes)	83.25	10.06	83.25	10.06	83.25	10.06
BE	Job accessibility (30 minutes) (1000s)	65.81	46.80	77.63	55.50	93.93	65.26
	Entropy index	0.42	0.18	0.42	0.18	0.42	0.18
	Public transit accessibility	14.11	24.78	14.30	25.17	14.49	25.60
	Public transit modal share	0.03	0.03	0.04	0.03	0.05	0.04

Table A-4 Summary statistics of SE and BE indicators at census tract level for South Shore (Region 4)

Category	Variable	Mean 1998	Std. Dev 1998	Mean 2003	Std. Dev 2003	Mean 2008	Std. Dev 2008
DV	ln of average household CO_2	2.90	0.32	2.77	0.48	2.81	0.36
SE	No. of full-time workers in HH	0.82	0.15	0.88	0.15	0.88	0.16
	No. of part-time workers in HH	0.64	0.09	0.60	0.07	0.60	0.07
	No. of persons under 15 years of age in HH	0.64	0.12	0.58	0.12	0.52	0.12
	No. of persons between 25 and 64 years of age in HH	1.60	0.16	1.54	0.16	1.50	0.16
	No. of persons 65 years of age and over in HH	0.23	0.09	0.25	0.09	0.27	0.10
	Average Household Income (1000s of CAD$)	52.67	10.68	57.08	12.33	59.71	13.40
	Household density (1000s/km^2)	2.14	2.82	2.37	3.18	2.74	3.81
	Intersection density (km^2)	28.34	26.01	44.78	59.28	44.78	59.28
	Travel Time to CBD (minutes)	61.22	17.51	61.22	17.51	61.22	17.51
BE	Job accessibility (30 minutes) (1000s)	47.15	39.48	54.13	42.62	61.76	47.77
	Entropy index	0.41	0.17	0.41	0.17	0.41	0.17
	Public transit accessibility	6.83	10.52	6.83	10.52	6.83	10.52
	Public transit modal share	0.05	0.03	0.06	0.04	0.08	0.03

Table A-5 Summary statistics of SE and BE indicators at census tract level for Longueuil (Region 5)

Category	Variable	Mean 1998	Std. Dev 1998	Mean 2003	Std. Dev 2003	Mean 2008	Std. Dev 2008
DV	ln of average household CO_2	2.48	0.24	2.25	0.32	2.08	0.41
SE	No. of full-time workers in HH	0.71	0.19	0.74	0.18	0.71	0.15
	No. of part-time workers in HH	0.62	0.11	0.58	0.10	0.58	0.10
	No. of persons under 15 years of age in HH	0.49	0.17	0.43	0.13	0.38	0.11
	No. of persons between 25 and 64 years of age in HH	1.48	0.28	1.40	0.23	1.35	0.20
	No. of persons 65 years of age and over in HH	0.24	0.10	0.28	0.10	0.32	0.10
	Average Household Income (1000s of CAD$)	48.41	15.45	52.03	17.72	53.09	18.52
BE	Household density (1000s/km^2)	0.69	1.01	0.72	1.09	0.79	1.28
	Intersection density (km^2)	107.77	72.09	391.05	404.63	391.05	404.63
	Travel Time to CBD (minutes)	36.67	6.35	36.67	6.35	36.67	6.35
	Job accessibility (30 minutes) (1000s)	193.63	81.47	215.44	92.72	238.26	96.36
	Entropy index	0.46	0.18	0.46	0.18	0.46	0.18
	Public transit accessibility	38.57	64.92	38.78	64.89	38.78	64.89
	Public transit modal share	0.21	0.06	0.22	0.07	0.23	0.07

Table A-6 OLS Model Estimation for Island of Montreal (Region 1)

No. of observations = 1,449; Adjusted-R^2 = 0.6602

Category	Variable	Coefficient	P-value
Socio-demographics	No. of full-time workers in HH	0.786530	0.000
	No. of persons under 15 years of age in HH	0.211100	0.000
	No. of persons between 25 and 64 years of age in HH	0.050166	0.000
	No. of persons 65 years of age and over in HH	0.260767	0.000
	Average Household Income (1000s of CAD$)	0.002720	0.000
Built Environment	Household density (km^2)	-0.001300	0.000
	Intersection density (km^2)	-0.000048	0.000
	Travel Time to CBD (minutes)	0.002134	0.000
	Job accessibility (30 minutes)	-0.000370	0.000
	Entropy index	-0.107935	0.000
	Public transit accessibility	-0.000412	0.000
	Public transit modal share	-0.521768	0.000
Year	Year	-0.043168	0.000
	Constant	1.800875	0.000

Table A-7 OLS Model Estimation for Laval (Region 2)

		No. of observations = 198; Adjusted-R^2 = 0.7325	
Category	Variable	Coefficient	P-value
Socio-demographics	No. of full-time workers in HH	0.654628	0.000
	No. of part-time workers in HH	0.083263	0.000
	No. of persons under 15 years of age in HH	0.237285	0.000
	No. of persons between 25 and 64 years of age in HH	0.041157	0.000
	No. of persons 65 years of age and over in HH	0.358062	0.000
	Average Household Income (1000s of CAD$)	0.001820	0.000
Built Environment	Intersection density (km^2)	-0.000665	0.000
	Travel Time to CBD (minutes)	0.004049	0.000
	Job accessibility (30 minutes)	-0.000620	0.000
	Entropy index	-0.073897	0.000
	Public transit accessibility	-0.000477	0.000
	Public transit modal share	-0.757035	0.000
Year	Year	-0.028784	0.000
	Constant	1.779753	0.000

Table A-8 OLS Model Estimation for North Shore (Region 3)

		No. of observations = 210; Adjusted-R^2 = 0.7125	
Category	Variable	Coefficient	P-value
Socio-demographics	No. of full-time workers in HH	0.160677	0.000
	No. of persons under 15 years of age in HH	0.117080	0.000
	No. of persons between 25 and 64 years of age in HH	0.553200	0.000
	No. of persons 65 years of age and over in HH	0.198417	0.000
	Average Household Income (1000s of CAD$)	0.004020	0.000
Built Environment	Intersection density (km^2)	-0.000838	0.000
	Travel Time to CBD (minutes)	0.003564	0.000
	Job accessibility (30 minutes)	-0.000370	0.000
	Entropy index	-0.251997	0.000
	Public transit accessibility	-0.000972	0.000
	Public transit modal share	-0.359704	0.000
Year	Year	-0.016894	0.000
	Constant	1.524119	0.000

Table A-9 OLS Model Estimation for South Shore (Region 4)

		No. of observations = 93; Adjusted-R^2 = 0.3285	
Category	Variable	Coefficient	P-value
Socio-demographics	Average Household Income (1000s of CAD$)	0.010700	0.000
Built Environment	Household density (km^2)	-0.018500	0.000
	Job accessibility (30 minutes)	-0.002150	0.000
	Entropy index	-0.949732	0.000
	Public transit modal share	-0.152004	0.000
Year	Year	-0.009601	0.000
	Constant	2.832955	0.000

Table A-10 OLS Model Estimation for Longueuil (Region 5)

		No. of observations = 198; Adjusted-R^2 = 0.7166	
Category	Variable	Coefficient	P-value
Socio-demographics	No. of persons between 25 and 64 years of age in HH	0.007451	0.001
	No. of persons 65 years of age and over in HH	-0.291048	0.000
	Average Household Income (1000s of CAD$)	0.007010	0.000
Built Environment	Household density (km^2)	-0.003500	0.000
	Intersection density (km^2)	-0.000262	0.000
	Travel Time to CBD (minutes)	0.007116	0.000
	Job accessibility (30 minutes)	-0.000550	0.000
	Entropy index	-0.178488	0.000
	Public transit accessibility	-0.000978	0.000
	Public transit modal share	-0.385168	0.000
Year	Year	-0.027401	0.000
	Constant	2.257891	0.000

Table A-11 Summary of CO_2 Estimates and Forecasts for Island of Montreal (Region 1)

Year/Scenario	Estimated with O-D survey data			Estimated & Forecasted with OLS Model		
	Total CO_2 (kt/day)	Number of Households	Average CO_2 (kg/hsld/day)	Total CO_2 (kt/day)	Number of Households	Average CO_2 (kg/hsld/day)
1998	6,435	768,950	8.37	6,758	768,950	8.79
2003	5,564	800,935	6.95	5,817	800,935	7.26
2008	4,838	826,265	5.86	4,708	826,265	5.70
2031 BAU				2,369	981,100	2.41
2031 PMAD				2,384	990,538	2.41
2031 MTQ				2,207	937,159	2.36

Table A-12 Summary of CO_2 Estimates and Forecasts for Laval (Region 2)

Year/Scenario	Estimated with O-D survey data			Estimated & Forecasted with OLS Model		
	Total CO_2 (kt/day)	*Number of Households*	*Average CO_2 (kg/hsld/day)*	*Total CO_2 (kt/day)*	*Number of Households*	*Average CO_2 (kg/hsld/day)*
1998	1,667	123,275	13.52	1,718	123,275	13.93
2003	1,631	132,300	12.33	1,632	132,300	12.34
2008	1,508	143,820	10.49	1,485	143,820	10.33
2031 BAU				1,179	190,469	6.19
2031 PMAD				1,123	200,533	5.60
2031 MTQ				1,230	200,618	6.13

Table A-13 Summary of CO_2 Estimates and Forecasts for North Shore (Region 3)

	Estimated with O-D survey data			Estimated & Forecasted with OLS Model		
	Total CO_2 (kt/day)	*Number of Households*	*Average CO_2 (kg/hsld/day)*	*Total CO_2 (kt/day)*	*Number of Households*	*Average CO_2 (kg/hsld/day)*
1998	3,262	170,750	19.10	3,341	170,750	19.57
2003	3,346	187,495	17.85	3,336	187,495	17.79
2008	3,498	217,165	16.11	3,475	217,165	16.00
2031 BAU				3,738	298,149	12.54
2031 PMAD				3,226	285,813	11.29
2031 MTQ				3,712	306,454	12.11

Table A-14 Summary of CO_2 Estimates and Forecasts for South Shore (Region 4)

	Estimated with O-D survey data			Estimated & Forecasted with OLS Model		
	Total CO_2 (kt/day)	*Number of Households*	*Average CO_2 (kg/hsld/day)*	*Total CO_2 (kt/day)*	*Number of Households*	*Average CO_2 (kg/hsld/day)*
1998	1,585	85,010	18.64	1,545	85,010	18.17
2003	1,545	92,855	16.63	1,666	92,855	17.94
2008	1,837	106,125	17.31	1,825	106,125	17.20
2031 BAU				3,420	200,874	17.03
2031 PMAD				3,004	193,271	15.54
2031 MTQ				2,511	139,043	18.06

Table A-15 Summary of CO_2 Estimates and Forecasts for Longueuil (Region 5)

	Estimated with O-D survey data			Estimated & Forecasted with OLS Model		
	Total CO_2 (kt/day)	*Number of Households*	*Average CO_2 (kg/hsld/day)*	*Total CO_2 (kt/day)*	*Number of Households*	*Average CO_2 (kg/hsld/day)*
1998	1,734	140,365	12.35	1,761	140,365	12.55
2003	1,521	146,620	10.38	1,542	146,620	10.52
2008	1,458	156,485	9.31	1,429	156,485	9.13
2031 BAU				749	196,424	3.81
2031 PMAD				532	197,027	2.70
2031 MTQ				788	202,575	3.89

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