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Exploring the link between the neighborhood typologies, bicycle infrastructure and commuting cycling over time and the potential impact on commuter GHG emissions

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ABSTRACT

This paper investigates the evolution of urban cycling in Montreal, Canada and its link to both built environment indicators and bicycle infrastructure accessibility. The effect of new cycling infrastructure on transport-related greenhouse gas (GHG) emissions is then explored. More specifically, we aim at investigating how commuting cycling modal share has evolved across neighborhood built-environment typologies and over time in Montreal, Canada. For this purpose, automobile and bicycle trip information from origin–destination surveys for the years 1998, 2003 and 2008 are used. Neighborhood typologies are generated from different built environment indicators (population and employment density, land use diversity, etc.). Furthermore, to represent the commuter mode choice (bicycle vs automobile), a standard binary logit and simultaneous equation modeling approach are adopted to represent the mode choice and the household location. Among other things, we observe an important increase in the likelihood to cycle across built environment types and over time in the study region. In particular, urban and urban-suburb neighborhoods have experienced an important growth over the 10 years, going from a modal split of 2.8–5.3% and 1.4–3.0%, respectively. After controlling for other factors, the model regression analysis also confirms the important increase across years as well as the significant differences of bicycle ridership across neighborhoods. A statistically significant association is also found between the index of bicycle infrastructure accessibility and bike mode choice – an increase of 10% in the accessibility index results in a 3.7% increase in the ridership. Based on the estimated models and in combination with a GHG inventory at the trip level, the potential impact of planned cycling infrastructure is explored using a basic scenario. A reduction of close to 2% in GHG emissions is observed for an increase of 7% in the length of the bicycle network. Results show the important benefits of bicycle infrastructure to reduce commuting automobile usage and GHG emissions.

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Introduction

Cycling has been praised for its ability to achieve short to medium utilitarian trips while essentially producing no externalities. In recognition of its many benefits, there has been a shift of focus from motorized travel toward the promotion of cycling in academia and policy circles alike. Several European countries namely Denmark, Germany and the Netherlands have been enjoying cycling booms and consequent benefits (Pucher et al., 1999). Meanwhile in Canada and the USA, cycling has remained a marginal mode of transport, with low modal share in most cities (Pucher and Buehler, 2006). While levels of utilitarian cycling in large North American cities are not comparable to those in Europe, Montreal is generally regarded as one of the North American leaders in urban cycling (Larsen and El-Geneidy, 2011).

In this study, we focus our attention on utilitarian uses of cycling, specifically for home-based work trips (i.e. commute trips). Similar to Wardman et al. (2007) and Caulfield (2014), the commuting market was selected because it represents a significant portion of trips that occur at peak hours when the externalities of private vehicle use are at their highest. Furthermore, the characteristics of commute trips are relatively stable over time, thus, a 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).

This paper aims to investigate how cycling modal split for commuting has evolved in different neighborhood types and between years in the city of Montreal. More specifically, this paper seeks to explore the effect of neighborhood built-environment typologies and bicycle infrastructure accessibility on commuting bicycle mode choice. Origin–destination (O–D) survey data for the year 1998, 2003 and 2008 are used for this purpose. Generally, built environment indicators that have been found to influence cycling; however, few studies have looked at the temporal evolution and the effect of bicycle infrastructure accessibility indicators. To represent the likelihood of cycling for commuting trips and its link to neighborhood typologies and bicycle infrastructure index, two regression techniques are used: (i) a binary logit model; and (ii) a simultaneous equation model. While the former does not account for residential self-selection bias, the latter does. Once the effects of BE and bicycle infrastructure are obtained, the reduction of greenhouse gas (GHG) emissions resulting from the construction of new cycling infrastructure is explored through simulation.

The paper begins with a literature review of the cycling and built environment literature including the methodologies used in this research. This is followed by the explanation of the data, variables and modeling approaches adopted for the research. Then, the results of each of the different approaches are presented and the effect of new cycling facilities on GHG emissions is estimated through simulation. The paper finishes with the reiteration of the key findings, as well as some avenues for future research.

Literature review

This paper is built upon the vast literature evaluating the effect of the built environment on transportation behavior. The built environment is a catch-all phrase to describe urban locations along a number of dimensions, initially as the 3-Ds (Cervero and Kockelman, 1997) of (population and employment) density, diversity (of land-uses) and design (e.g. road network structure), and later expanded to include destination accessibility (Handy, 1993) and distance to transit, among others. The literature is so extensive that there have been several review papers on the topic, with Ewing and Cervero (2001) and Ewing and Cervero (2010) being the most well-known. This literature has looked at many different aspects of travel behavior including VMT (vehicle miles traveled), number of trips, and mode choice. The most relevant literature for this research considers the effect of the built environment on active transportation, and cycling in particular. Even though the body of literature is quite large, it has typically been focused on active transportation more generally and not explicitly about cycling (e.g. Handy et al. (2002)). The research presented here concerns itself with the literature on the effect of the built environment on cycling mode choice.

As it turns out, there has been a fair bit of recent interest in the factors that influence bicycle mode choice more broadly. Some of that literature, while interesting, focuses on the factors affecting bicycle mode choice, but not on built environment factors (e.g. Wardman et al., 2007; Heinen et al., 2013). The literature of interest here, however, focuses on the effect of the built environment on bicycle use.

Much of this literature (although not all – e.g. Dill and Voros (2007), Stinson and Bhat (2004) and Caulfield (2014)) analyzes the effects of the built environment on cycling with logit models, and other variants of these models (Cervero and Duncan, 2003; Cervero et al., 2009; Moudon et al., 2005; Ortuzar et al., 2000; Parkin et al., 2008; Plaut, 2005; Titze et al., 2008; Wardman et al., 2007; Winters et al., 2010; Pinjari et al., 2007). This analysis is conducted by including built environment variables in logit models of bicycle mode choice and estimating effect sizes based on the coefficients associated with these variables. In more recent studies done by Goodman et al. (2014, 2013), they have looked at the effect of bicycle sharing systems on normalizing the image of cycling (as a safe mode) and also examined how adults use new walking and cycling routes, in London, UK. Aldred and Jungnickel (2014) investigate the role culture can play in transport policy and specially cycling. They show how local cultures in UK shape the experience and understanding of cycling. Sahlqvist et al. (2015) also look at use of new walking and cycling infrastructure in 3 cities in UK.

A complicating issue in the analysis of the effect of the built environment on mode choice, including cycling mode choice, is the phenomenon known as residential self-selection bias. Due to the fact that people who like to cycle are more likely to choose to live in locations that are more amenable to cycling (i.e. with high population density, etc.), there is concern that the effect of built environment variables may also be capturing this effect. There is a fair bit of literature dedicated to this question, and several methods have been developed to account for it when estimating the effects of the built environment on mode choice (see e.g. Cao et al. (2010)). As such, some studies on the built environment and bicycle mode choice have accounted for residential self-selection (e.g. Pinjari et al. (2007)), although by no means all. When it has been done, it has been through the use of joint models, which simultaneously model residential location choice and mode choice.

Furthermore, while there has been some interest in examining cycling behavior across time (e.g. Caulfield (2014)), for the most part, built environment and bicycle mode choice studies are static, taking place at one period in time and therefore the extent of the literature does not fully address the topic of this paper. Finally, the effect of new cycling infrastructure on the reduction of transportation GHG emissions as a tool to mitigate climate change has been discussed in literature a few times. For instance, one can refer to Goodman et al. (2014, 2013) and Brand et al. (2014) that offer a detailed review on this topic.

As such, this research attempts to fill in some of the gaps in the existing cycling and built environment literature. In particular, it seeks to examine the ridership evolution and the effect of the built environment typologies on cycling mode choice while controlling for residential self-selection. A simultaneous equations model approach is implemented to estimate neighborhood choice and bicycle commute mode choice as a joint decision, and by considering data across three periods of different origin–destination (O–D) surveys from Montreal, Canada. In addition, the potential impact of bicycle facilities on GHG reductions is illustrated through a basic scenario that would result from the installation of planned cycling infrastructure.

Methodology

The methodology consists of four steps: (i) defining and generation of built environment and network connectivity indicators; (ii) preparing data including generating neighborhood typologies and cycling facilities over time; (iii) performing model parameter estimation for cycling mode choice vs other modes; and (iv) evaluating the effect of proximity to new bicycle facilities on GHG emissions using GHG emission calculations done previously by Zahabi et al. (2012) and Zahabi et al. (2013).

Built environment indicators

This study adopted a methodology developed by Harding et al. (2012) and Zahabi et al. (2012), which applied a weighted 500 m 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. *K*-means statistical clustering is used in order to regroup households into "*K*" homogenous clusters by five indicators ((i) population density; (ii) employment density; (iii) cycling network density;(iv) public transit accessibility; and (v) land-use mix). The goal of using this technique is to maximize the inter-cluster variation while minimizing intra-cluster variation. The objective is therefore to assemble households into *k* number of groups having similar values for the five indexes in their neighborhoods. After several attempts, it is decided that five clusters is a satisfactory number (five different types of neighborhoods) so that each has an acceptable number of households (more than 1%) and for sufficient variation between clusters. This has been done in STATA.

Calculating the indicators at the grid cell-level minimizes the potential of distorted results associated with scale and modifiable areal unit problems (Harding et al., 2012; Zahabi et al., 2012). Weights were applied to average cell values using surrounding contiguous cells to avoid peaks as seen in Harding (2013) and Harding et al. (2012).

Population and employment densities

We used the population and employment count data at the census-tract level from Statistics Canada for census years 1996, 2001 and 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 calculated as the population/employment counts per square kilometer of land.

Cycling network density

Cycling infrastructure data was obtained from the city of Montreal and Vélo Québec, a provincial cycling agency. Some revisions were made to ensure that the cycling infrastructure over time was accurately reflected using ArcGIS 10.1.

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 (Harding et al., 2012; Zahabi 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. This is computed as $PT_j = \sum_{i=1}^{n}\left(\frac{1}{d_{ij}\times h_i}\right)$, where PT_j refers to public transit accessibility at cell j, d_{ij} is the 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), and h_i = average headway (hours) of line i during AM peak (maximum value of 1 h).

Land use mix

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) 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 were water and open area (Zahabi et al., 2012). The following equation was used $E_j = \sum_{i=1}^{n}\frac{\left[\left(\frac{A_{ij}}{D_j}\right)\ln\left(\frac{A_{ij}}{D_j}\right)\right]}{\ln(n)}$, 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).

Network connectivity indicators

Intersection (node) density

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 because we 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 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 (Deb and Trivedi, 2006).

Link to node ratio

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

Distance to cycling infrastructure

The tangent distance in kilometers to the nearest cycling lane from an individuals' residence was calculated. It was assumed that the greater the distance, the greater the likelihood of a resident choosing not to cycle.

Model calibration

The outcome of interest here is the commuting bicycle mode choice vs other modes. This can be typically represented as a dummy (0/1) variable. Therefore, a binary logistic regression model approach is adopted to investigate the link between built environment and network connectivity indicators with the outcome of interest. The model outcomes were expected to answer two questions: (i) what were the effects of built environment and network connectivity indicators on cycling over the entire study period, while controlling for other explanatory (socio-demographic) variables; and (ii) how did cycling evolve over the study period. In this model, the reference neighborhood typology and year were set to urban-suburb (3) and 1998, respectively.

The binary logit model allowed us to quantify the effects of neighborhood typologies on cycling levels as well as its evolution, while controlling for other factors. However, the standard binary logit model does not take residential self-selection into account. In the literature, there is an increasing evidence for the endogeneity of mode choice and residential location choice. In practice, and often in research, residential location and mode choice are assumed to be independent choices. Residential location choice has been modeled as a function of demographic, market housing and prices, employment location and accessibility measures, while mode choice has been modeled as a function of mode-specific attributes, socio-demographics and built environment characteristics at the residential location. There is, however, increasing evidence that households select a neighborhood that allow them to pursue their activities using modes that are compatible with their socio-demographics (e.g., income, car ownership, life cycle) and travel preferences (e.g., preference for the use of a particular mode or short commuting travel times). This phenomenon is generally referred to as residential self-selection or residential sorting – for additional details, see TRB (2009). Ignoring the dependence of these choices, when they are not independent, can result in the identification of false causal effects of built environment attributes on mode choice. In order to test the potential presence of self-selection, we model jointly the two outcomes, neighborhood typologies representing residential location choice and mode choice, as endogenous choices (TRB 2009). In other words, a simultaneous equation model (SEM) approach is also applied to the same data. This type of model allows to simultaneously estimate the effect of built environment on the choice of mode as a binary outcome taking into account the presence of endogeneity. For this purpose, we adopted the methodological approach used by Dill et al. (2004) and Goodman et al. (2014). In this model, individuals are assumed to choose simultaneously where to live and what mode of transport (bicycle vs other) they use for their home-based work trips. Eqs. (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. This assumption is correct insofar as the observed variables capture the effects of preferences and attitudes common to residential location and travel behavior. The model was estimated in STATA 10.1 (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 Eq. (3), with the normalization structure.

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

$$N_{ij} = \beta_i z_i + \delta_j l_{ij} + \eta_{ij} \tag{2}$$

$$Pr(K_{ij}|x_i, l_{ij}) = \frac{\exp(\beta_j z_i + \delta_j l_{ij})}{\sum_k^j \exp(\beta_k Z_i + \delta_k l_{ik})} \tag{3}$$

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, $j = 1, \ldots J$
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)

Cycling infrastructure effects on transport-related GHG emissions

In the network connectivity indicators discussed in the previous section, there is a variable named 'distance to nearest cycling infrastructure' – which represents the distance to the closest cycling path or lane from an individual's residence. This variable was expected to have a negative coefficient, meaning, that an increase in distance to the nearest cycling infrastructure would result in a reduction of the probability to cycle to work. With this in mind, the idea here was to explore the potential impact of improvements in cycling infrastructure accessibility not only on bicycle mode choice, but also on transport-related GHG emissions.

At the time of the study, the most recent O–D survey data available was for the year 2008. However, information on cycling infrastructure that the city of Montreal has already built or has planned to have built by the end of 2014 was available. Using this data on individuals in our dataset, we wanted to capture the GHG emissions reduction on individual commuter trips due to the change in the proximity to these infrastructures. In order to have a better grasp on the changes between the cycling facilities between the two periods, a map has been generated (see Fig. 1). For the GHGs impact simulation, Biogeme[1] software was used since it has a simple routine to simulate choices made based on the estimated models. The steps taken toward this objective were as follows:

(1) The same coefficients as those from STATA (in the previous section) were used in Biogeme to simulate bicycle mode choice.
(2) Then, the 1998 and 2003 (first two O–D years) data were eliminated for the simulation process.
(3) For the remaining 2008 data, the variable of interest (distance to nearest cycling infrastructure), which had 2008 information was replaced with 2014 data.
(4) Then, the modal shift was simulated using Biogeme's simulation tool. This was done for 1000 simulations. In this step, Biosim (model simulation tool which comes with Biogem) is used in which for every simulation the logit model predicted coefficients were used and all the values were kept the same, except for proximity to cycle tracks. Using this new utility value, this tool predicts the probability of cycling versus other modes and assigns a simulated value to the predicted mode used by that individual in that simulation.
(5) From prior research on passenger transport GHG emissions by Deb and Seck (2009) and Goodman et al. (2014) an inventory of GHG emissions produced by each of the individuals in O–D survey was used. The new GHG emissions based on modal shifts (cycle to other, or other to cycle) were estimated for these individuals (for all 1000 simulations) and the change in total expanded GHG emissions were reported. A conservative approach was implemented so that individuals who switch from bike were assigned to car (unless they did not own a car). A brief methodology (as explained in Deb and Seck (2009) and Goodman et al. (2014) on the GHGs estimation method is explained below.

[1] http://biogeme.epfl.ch/home.html

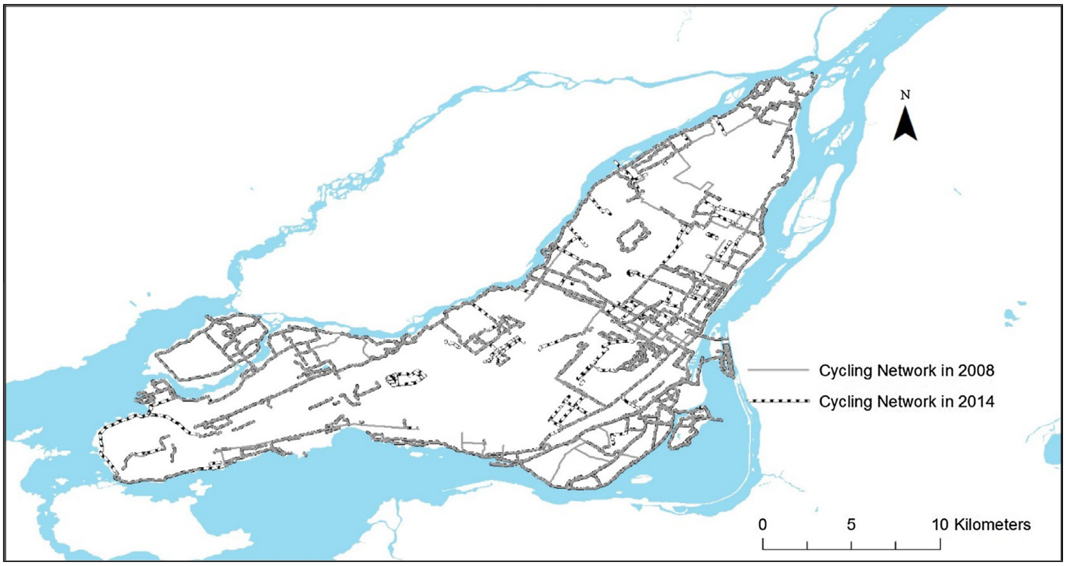

Fig. 1. Cycle tracks in 2008 vs. 2014.

Trip-level GHGs

For each trip in the three O–D surveys (1998, 2003 and 2008), two GHG emitting mode categories are distinguished; private motor vehicles and public transit including transit buses and commuter trains. Some trips can involve more than one mode. The procedure for GHG emissions estimation is described as follows:

(i) From a traffic assignment model developed and calibrated by the Quebec provincial ministry of transportation (MTQ) (Babin, 2006), congested (at equilibrium) times for each link of the road network were obtained along with their distances. Link travel times were obtained for different periods of the day, during morning and afternoon peak hours, and out of peaks.[2]
(ii) Each trip was associated (according to its departure time) to a particular period (network) and travel times described in the previous step. The shortest path (based on user-equilibrium times) was then calculated for each trip to obtain route, link distances and speeds for each link. Note that travel times are directional on the network for the traffic assignment model.
(iii) For each trip and emitting mode, ridership, fuel consumption rates and emission factors were calculated.
(iv) Overall GHG emissions for each trip were then calculated according to Eqs. (6) and (7) below.

For trips involving motor vehicle as a unique or combined mode, the emissions were estimated using distance and average speed at the link level, vehicle fuel consumption rate (FCR) at the FSA-level, and GHG emission factors. This procedure is detailed in Barla et al. (2009) and Zahabi et al. (2015).

Emissions for a given trip j departing in a particular hour t is estimated as:

$$GHG_{Ajt} = \sum_{i=1}^{N} [SP_{ijt} \times D_{Aij}] \times \frac{FC_{Aj} \times EF_A}{R_{Aj}} \tag{4}$$

where

A – Automobile
i – Link ($i = 1, \ldots, N$ links used by trip j)
j – Trip
t – Departure time (hour)
GHG_{Ajit} = GHGs for automobile trip j (in kg of CO_2) departing at time t.
D_{ij} = Travel distance on segment (link in network) i in 100 km.
SP_{ijt} = Speed correction factor for segment i of trip j departing at time t. Since fuel consumption also depends upon speed, speed correction factors developed by the MTQ were also used. These factors were produced after a local calibration of

[2] Note that the 2008 MTQ model has hourly speed data (for an entire 24 h). However, for the year 2003, the 24 h period was divided into 5 sub-periods (0–6; 6–9; 9–15:30; 15:30–18:30; 18:30–24) and for the year 1998, the periods are 3 for AM & PM peak (6–9 and 15:30–18:30), and off-peak. The 2008 travel times was aggregated in similar intervals to 2003.

MOBILE6 (for further details, see Babin et al., 2004). Link speed was matched with its corresponding speed correction factor.

FC_{Aj} = Average fuel consumption rate (FCR) in litres of gasoline/100 km for the vehicle used in trip *j*. This was generated using the motor-vehicle fleet inventory of the automobile insurance corporation of Quebec (SAAQ). For further details see (Barla et al., 2008). This inventory contains the make, year and model of each vehicle in the province as well as the fuel consumption rate per km. However, the address of the vehicle is provided at the FSA (3-digit postal code). Therefore, FCR values at the FSA were generated. An FCR is then associated to each vehicle belonging to the same FSA.

EF_A = Emission factor for gasoline (2.289 kg of CO_2/l of gasoline). This is obtained from the national inventory report by Environment Canada.[3] Although this number is fixed for all gasoline vehicles for CO_2, for other GHG emissions such as CH_4 and N_2O, the emission factor depends on the type of vehicle (e.g. Light duty, heavy duty, Oxidation Catalyst, non-catalytic controlled, etc.). Since information regarding the type of vehicle owned by the household was not obtained, emissions of other GHGs were not estimated.

R_{Aj} = Number of passengers in trip *j*, including the driver. This is determined from the O–D survey data. Car trips in the same household, departing at the same hour and with the same origin–destination are associated to the same motor-vehicle trip.

Other factors such as cold starts and cold temperatures are not considered mainly because local cold-start adjusting factors and required vehicle level information are not available. Moreover, in our recent paper (Zahabi et al., 2014), the effect of cold starts was found to be relatively small in stable weather conditions and for gasoline light duty vehicles. During winter and for hybrid-electric vehicles (HEVs) the effect of cold starts can be more severe. In this study, since O–D surveys are implemented in the fall, our GHG estimates are representative of a typical day in the fall season. That is, our inventories are representative of a fall day where the effect of cold starts is expected to be small.

For uni-modal or multimodal trips involving public bus transit and/or commuter trains, GHGs are estimated in a similar fashion. In this case, however, average speeds at the trip-level are used since link-level speeds were not available, but this speed estimate considers congestion. For additional details refer to our recent work (Zahabi et al., 2014, 2015).

To obtain the household inventory, GHGs are estimated for each uni-modal and multimodal trip in the O–D surveys. Trip level emissions are then aggregated at the individual and household level.

Data

O–D survey data

Origin–destination (O–D) travel surveys from Greater Montreal for 1998, 2003 and 2008 were the primary source of travel data. The O–D survey, which takes place every five years, provides urban travel information for an average weekday for residents of Montreal (Agence Métropolitaine de Transport (AMT), 2008). The survey was 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. For each survey, 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 the trip origin, trip destination and trip-maker residence, mode(s) of travel, purpose of trip, socio-demographic characteristics of the individual being interviewed and his household, time of departure, expansion factor of individual, etc.

Since 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 both full- or part-time employees and who made a work-related trip during the survey period were included in the analysis. The selected number of individuals for this study was 21,188 (1998), 20,170 (2003), and 19,508 (2008).

Neighborhood typology generation

A map of the distribution of the clusters is presented in Fig. 2 and the built environment characteristics for the neighborhood typologies are presented in Table 1. The five clusters used are as follows:

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

[3] National Inventory Report 1990–2009 (2011 submission), Environment Canada. (http://www.ec.gc.ca/ges-ghg/default.asp?lang=En&n=AC2B7641-1)

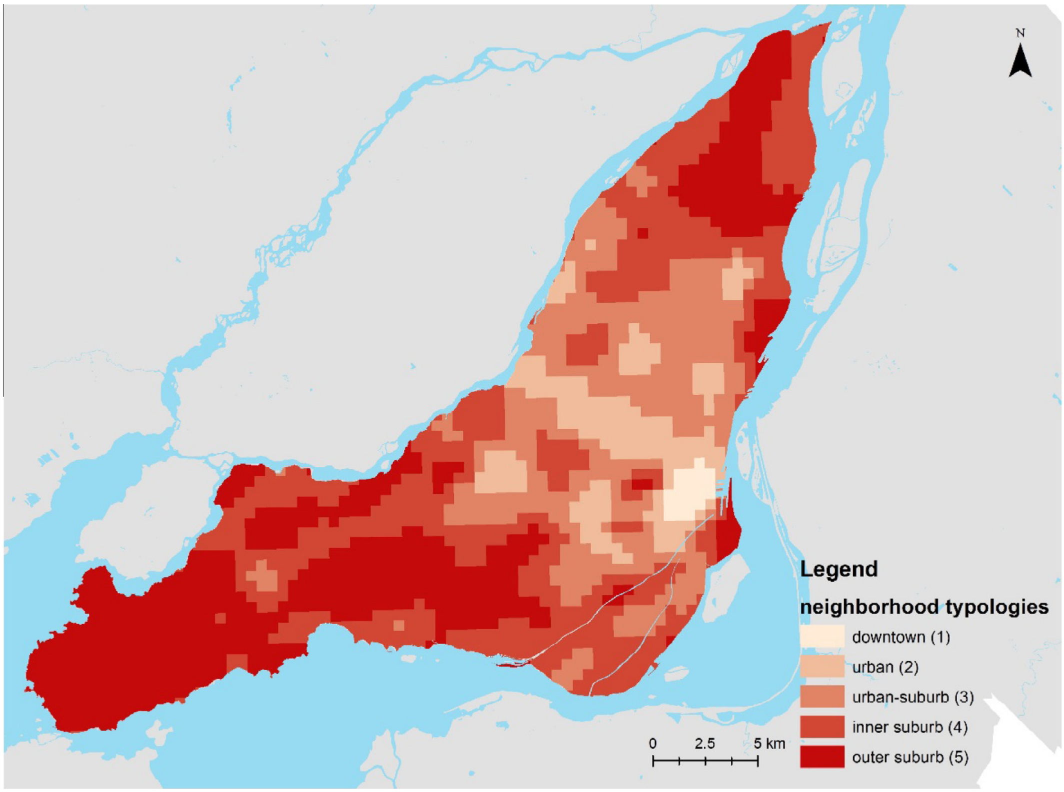

Fig. 2. Neighborhood typologies.

– 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.

The second part of Table 1 shows the cycling, walking and active transport modal share for each of the neighborhood typologies. It is interesting to see that neighborhood type 'urban' (2) has the highest cycling levels, while 'downtown' (1) has lower cycling levels than the mean for the entire island of Montreal. The low cycling levels in 'downtown (1)' may be explained by a 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.

Results

Akaike Information Criterion (AIC) values are presented in Table 2 to compare the goodness-of-fit of each of the fitted models. The AIC value of the simultaneous model was smaller than the standard logit models (173,211.7 vs. 173,223.5). This indicates a slightly better fit of the simultaneous equation model compared to the logit model.

The results of the binary logit model are presented in Table 3. For continuous variables, the elasticities represent the percentage change in the probability of cycling if the value of the explanatory variable is increased by 1%. Whereas, for dummy variables, the effect size represents the percentage change in the probability of cycling if the explanatory variable of interest is in effect.

For household-level characteristics, individuals that live in a household with private vehicles had 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 were less likely to cycle by 35–65% than individuals who had no access to cars in their households. This finding is similar to the findings by Cervero et al. (2009), who found that the number of vehicles in the household is negatively associated with cycling. The coefficient of this variable in their model was −0.7. In a study of non-motorized commuting in the US by Titze et al. (2008), it was found that individuals living in a household with no cars was positively associated with the

Table 1
Modal share of walking and cycling on Island of Montreal.

Variable	Downtown (1) 1998 (%)	2003 (%)	2008 (%)	Δ (%)	Urban (2) 1998 (%)	2003 (%)	2008 (%)	Δ (%)	Urban-suburb (3) 1998 (%)	2003 (%)	2008 (%)	Δ (%)	Inner suburb (4) 1998 (%)	2003 (%)	2008 (%)	Δ (%)	Outer suburb (5) 1998 (%)	2003 (%)	2008 (%)	Δ (%)	Island of Montreal 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

	1998	2003	2008	1998	2003	2008	1998	2003	2008	1998	2003	2008	1998	2003	2008	1998	2003	2008
Population density	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	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	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	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

Table 2
Comparison of AIC.

Methodology	Model type	AIC	LR test	
			Coefficient	*P*-value
Binary logit	Neighborhood and year, separately	10,383	1279	0.000
	Neighborhood-year pairs	10,940	1284	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	6817	0.000

Table 3
Results of binary logit model – separate neighborhood typologies and year effects.

Category	Variable	Coefficient	Std. error	*P*-value	Elasticity/effect size (%)
Socio-demographics	0 car per adult in HH	(reference)			
	0–1 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)			
	15–24 yrs old	0.8244	0.1685	0.000	39.0
	25–34 yrs old	1.0013	0.1427	0.000	46.2
	35–44 yrs old	1.1688	0.1415	0.000	52.6
	45–54 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)			
Connectivity indicators	Distance to cycling infrastructure (km)	−0.4885	0.0586	0.000	−3.71
	Intersection density	0.0097	0.0019	0.000	7.95
	Link to node ratio	1.6090	0.2039	0.000	38.17
TRIP characteristics	Commute trip distance squared	−0.0004	0.0001	0.001	−32.84
	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	–

probability of cycling to work (coefficients 1.0–3.1), while owning two or more cars had the opposite effect. In more recent studies by Goodman et al. (2014, 2013), Brand et al. (2014) and Sahlqvist et al. (2015) have looked at broader and wider range of (continuous) outcome measures – also making distinction between utility and leisure cycling (and walking) – the evidence is consistent with what we found.

In terms of individual-level socio-demographics, we found that gender, age and employment status influenced cycling levels. Similar to the findings of Heinen et al. (2013), Titze et al. (2008) and Cervero et al. (2009), the likelihood of cycling was positively associated with being male, as males were more likely to cycle to work by 31% than females. Employment status influenced cycling levels as full-time employees were less likely to cycle than part-time employees by 16%. It was found that the highest effect sizes were attributed to an individuals' age, where the probability of cycling to work doubled if individuals were between the ages of 35 and 44 compared to the probability if the individuals were older than 54. In general, individuals between the ages 25 and 54 years were found to cycle significantly more relative to young adults and seniors.

The second category of variables was built environment and bicycle network connectivity indicators. As expected, an increase in the distance to the nearest cycling facilities from a residence reduces the probability of individuals choosing to cycle to work. Based on the elasticities, a 10% decrease in distance to nearest cycling facilities (measured in km) would on average result in a 3.7% increase in the probability of choosing to cycle. Similarly, Cervero et al. (2009) found that an increased pedestrian/bike-friendly design factor at the origin increased the likelihood of an individual choosing to cycle to work. On the other hand, Stinson and Bhat (2004) found that objective measures of proximity to off-street trails and bike lanes were 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% modal share in 2008).

Furthermore, intersection density and the link to node ratio of residential location were found to be positively associated with the choice of cycling to work, suggesting that street design with higher connectivity improves cycling levels. Similar findings have been made by Moudon et al. (2005) who determined that medium to high street densities were associated with more cycling.

The third category of variables was trip characteristics, which included commute distance and departure times. Similar to previous literature (Heinen et al., 2013), the negative coefficient of 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 et al., 2009).

Evolution of cycling and effects of neighborhood typologies

Starting with the results of the simple binary logit model (Table 3), we see that the likelihood of cycling has increased with time. Relative to 1998, the likelihood of cycling to work increased for individuals living in 2003 and 2008 by 4 and 19%, 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 high elasticities for the year variables can be explained by the following (but not limited to): (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 toward cycling. Many studies on the behavioral aspects of cycling have found a phenomenon of a positive feedback cycle which prevails in many large cities (Zahabi et al., 2013). Essentially, it has been found that promotional efforts for cycling (such as improvement of cycling facilities) increase cycling levels as well as safety.

The results of the SEM (mode choice) are presented in Table 4. The model which represents the choice of neighborhood typology of residence has not been reported due to space limitations. 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) caused 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) decreased the likelihood to cycle to work by 58%, 20%, and 11%, respectively. 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) decreased the likelihood of cycling to work by 58%, 22%, and 6%, respectively. It is worth mentioning that including other explanatory variables such as car parking and public transit availability and costs, and health status (perceived health) would add to the strength of the model, but unfortunately this data was not available at this level for our study.

Socio-demographics

In Table 4, for household-level characteristics, living in a household with private vehicles is associated with decreased likelihood to cycle to work. In fact, individuals who live in a household with cars were less likely to cycle more by 35–52% than individuals who had 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, and were thus excluded in the SEM. In terms of individual-level socio-demographics, similar influences were found in the SEM compared with the binary logit model. 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 cycle by 31% and being employed full-time instead of part-time decreased the likelihood to cycle by 16%. Once again, the highest elasticities were attributed to an individuals' age, where the likelihood of cycling to work more than doubled if individuals were between the ages of 35 and 44 relative to if the individuals were 55 years old or older. 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.

The second category of variables was network connectivity indicators (Table 4). The results are consistent with those of the binary logit models. In terms of distance to the nearest cycling infrastructure, a 10% increase of this variable would reduce the probability of choosing to cycle to work by 3.7%. A 10% increase in intersection density and link to node ratio of residential location would increase the likelihood to bicycle to work by 8 and 38.5%, respectively. Once again, these results confirm that street design and street connectivity are positively associated with cycling levels.

Table 4
Results of mode choice of SEM.

Category	Variable	Coefficient	Std. error	*P*-value	Elasticity/effect size (%)
Socio-demographics	0 car per adult in HH	(reference)			
	0–1 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)			
	15–24 yrs old	0.7980	0.1682	0.000	37.9
	25–34 yrs old	0.9861	0.1426	0.000	45.6
	35–44 yrs old	1.1586	0.1416	0.000	52.2
	45–54 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)			
Connectivity indicators	Distance to cycling infrastructure (km)	−0.4929	0.0587	0.000	−3.7
	Intersection density	0.0098	0.0019	0.000	8.0
	Link to node ratio	1.6210	0.2044	0.000	38.4
Trip characteristics	Commute trip distance squared	−0.0004	0.0001	0.001	−32.8
	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	–

The third category of variables was trip characteristics, which included commute distance and departure times (Table 4). Airline commute distance was found to be negatively associated with utilitarian cycling. Furthermore, the likelihood to cycle to work increased by 39% for departure times between 8:31 and 9:30 AM. Once again, a strong positive association between an individuals' likelihood to cycle and departure times after 7:30 AM was found.

Investigating the effect of proximity to cycling facilities on biking and emissions

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. With respect to this issue, as mentioned in the methodology section, the inclusion of new cycling infrastructure in 2014 was modeled as the distance to a cycling facility and used in the model to forecast the likelihood of biking in each neighborhood type. This result is then used to estimate resulting reductions in GHG emissions from these simulations. The results are reported in Fig. 3. We can observe that the average of the distribution is −1.8% and the standard deviation is 0.16.

In general, the results indicate that there would be a reduction in GHG emissions resulting from new cycle track infrastructure. This reduction (−1.7%) would be as big as converting all the transit buses to hybrid technology and electrifying the commuter trains in Montreal at the same time (Dill et al., 2004; Zahabi et al., 2013). For instance, in Montreal, currently, modal split in terms of trips is 60% for cars, 23% for transit, 15% walking and 2% bikes in 2013. In terms of GHGs, cars represents 95% and transit represents 5% in Montreal. For the scenario we are evaluating, we consider the network of 2008 with 603 km of bicycle facilities, and we estimate the modal change (car to bike) assuming the new condition of the network in 2014, which is now 648 km. This increase in infrastructure represents about a 2% reduction in GHGs from car trips. This decrease is similar to the one that would be generated through the replacement of the diesel bus fleet with hybrid electric technologies. However, in terms of cost this would be very different, a 40-foot hybrid bus costs around $450,000 (Canadian) which is equivalent to approximately 5.5 km of bicycle facilities (cycle tracks).

It is worth mentioning that these results should be used with caution due to some of the limitations in the analysis such as not having a control group or not having used a before-after observational approach. It is very likely that more work trips will take place (with either bike or other modes) since the expansion of the bicycle network would increase the overall utility of cycling. However, our approach was not able to account for that. Also, with respect to the change in mode resulting in

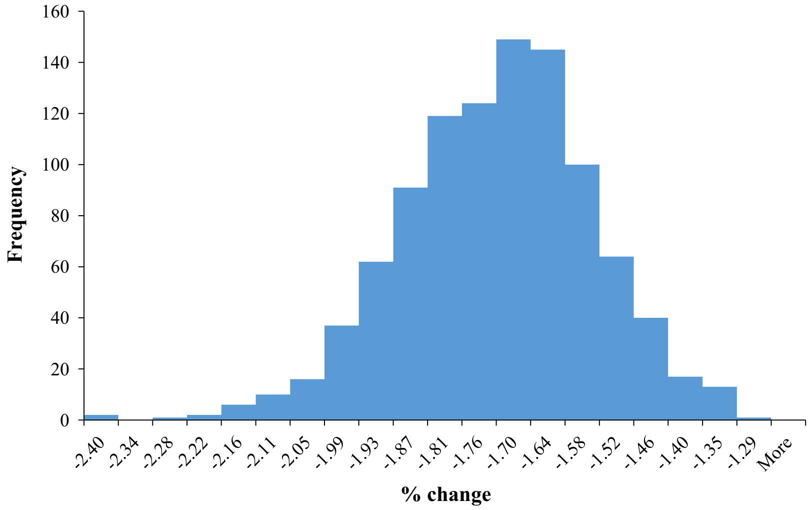

Fig. 3. Histogram of GHG reduction due to 2014 cycle tracks.

changes in GHG footprint, a conservative approach was implemented so that individuals who switch from bike were assigned to car (unless they did not own a car). In addition, bicycle culture environmental concerns and weather are other factors that can influence commuting cycling and we did not take them into account.

Conclusion and future work

This paper presented some empirical evidence on the effects of the built environment, as described through neighborhood types and network connectivity indicators, on cycling over time. For this study, large samples 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 that there is a general increase in the likelihood of commuting by bicycle over time in Montreal. In fact, the 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 experienced the greatest growth of 2.5% and 1.6% over the 10 year period, respectively (Table 1). The built environment of the study region has not evolved significantly during the ten-year study period. As a result, the observed change in cycling activity can be explained by attitudinal and cultural changes in the population, along with the increase of bicycle infrastructure 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. As has been documented elsewhere, this is possibly caused by promotional efforts by local municipalities and agencies which appear to have positively influenced cycling activity.

As in other studies, it is found that cycling infrastructure accessibility is positively linked to bicycle usage, playing a positive role in reducing transportation GHG emissions, by shifting the mode share of bikes. Although this effect may appear small (about −1.7%), it is as big as the estimates we have found in our previous research when converting all the transit diesel buses to hybrid technology and electrifying the commuter trains in Montreal at the same time (Dill et al., 2004; Zahabi et al., 2013). This is to say that the GHG benefit from adding low-cost new cycling infrastructure can be as important as other more costly strategies.

One of the limitations of the research is that only three waves of data over time were used. As preference survey data was not available, our models were not able to control for individual 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 controls for socio-demographics and the built environment attributes by including related variables in the models. However, both active and public transportation activity levels merit exploration in order to obtain more insight into sustainable commuter behavior and methods and strategies to enhance that. We also have to point out the assumption we made with respect to stable unit value treatment. The assumption here is that the units are not interacting over time. Another important limitation of this research is that we only examined the built environment at the origin of the trip and did not consider the neighborhood environment of the route or the destination of the trip. With respect to the GHG estimation change due to the change in proximity to cycle tracks, we have to point out that it is very likely that more work trips that did not initiate before, now will take place (with either bike or other modes) since the expansion of the bicycle network would increase the overall utility of cycling, although our approach was not able to account for that. Also, with respect to the change in mode resulting in changes in GHG footprint, a conservative approach was implemented so that individuals who switch from bike were assigned to car (unless they did not own a car). By assuming the switch from biking to car (rather than public transit or walking), we are overestimating the GHG footprint for the 2014 cycle track scenario. Also, note that O–D surveys are implemented at the end of the fall (Oct–Nov period) when bicycle ridership is decreasing significantly and represents about 67% of the ridership (Nosal, 2015). This, however, points to our estimates being more conservative than they probably are in reality. Finally, it would have been ideal to control for weather and elevation changes. However, due to data restrictions, this was not possible in our analysis.

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