

Impact of ICT access on personal activity space and greenhouse gas production: evidence from Quebec City, Canada

Luis F. Miranda-Moreno

Assistant Professor

Department of Civil Engineering and Applied Mechanics
McGill University, Montréal, Québec
Canada H3A 2K6

E-mail: luis.miranda-moreno@mcgill.ca

Naveen Eluru

Assistant Professor

Department of Civil Engineering and Applied Mechanics
McGill University, Montréal, Québec
Canada H3A 2K6

E-mail: naveen.eluru@mcgill.ca

Martin Lee-Gosselin*

Emeritus Professeur

École Supérieure d'Aménagement du Territoire et de Développement Régional,
and Centre de Recherche en Aménagement et Développement

Université Laval, Quebec City

Canada G1K 7P4

*Corresponding author:

E-mail: Martin.Lee-Gosselin@crad.ulaval.ca

Fax: +1 418 656 2018

Phone: + 1 418 828 9918

Tyler Kreider

Research Assistant

Department of Civil Engineering and Applied Mechanics
McGill University, Montréal, Québec
Canada H3A 2K6

E-mail: tyler.kreider@mail.mcgill.ca

ABSTRACT: This paper presents an approach to investigating the impact of information and communication technologies (ICTs) on travel behaviour and its environmental effects. The paper focuses on the spatial dispersion of out-of-home activities and travel (activity space) and greenhouse gas emissions (GHGs) at the level of the individual. An original method, combining spatial analysis in a geographic information system (GIS) with advanced regression techniques, is proposed to explore these potentially complex relationships in the case of access to mobile phones and the Internet, while taking into account the influence of socio-economics and built environment factors. The proposed methodology is tested using a 7-day activity-based survey in Quebec City in 2003-2004, a juncture of particular interest because these ICTs had recently crossed the threshold of 40% (mobile phone) and 60% (home-based Internet) penetration at the time. The study period also largely pre-dates the era of *mobile* Internet access. Among other results, socio-demographic factors were found to significantly affect both ICT access and travel out-comes. The built environment, represented by neighbourhood typologies, also played an important role. However, it was found that after controlling for the self-selection effect, built environment and socio-demographics, those who had a mobile phone available produced 30% more GHGs during the observed week than those who did not. This higher level of GHG production was accompanied by a 12% higher measure of activity dispersion. On the other hand, having Internet access at home was associated with lower GHGs (-19%) and lesser activity dispersion (-25%). Possibly, mobile phones enable individuals to cover more space and produce more emissions, while the Internet provides opportunities to stay at home or avoid motorized travel thus reducing emissions. The estimated effects of having a mobile phone were not only negative but also larger in magnitude from the environmental point of view than those of fixed Internet access. However, the results of this study also suggest that access to mobile phones and Internet may have substantial and compensatory effects at the individual level that are undetected when using model structures that do not take into account that unobserved factors may influence both ICT choices and travel outcomes.

1. INTRODUCTION

A number of earlier studies of Information and Communication Technologies (ICT) and individual travel behaviour have provided useful insights into the complex relationship between ICTs and travel patterns. However, past research has mainly focused on the impact of ICTs on activity and travel outcomes such as number of trips, number of activities (total or per-capita) and distance travelled: Bhat et al (2003), Kim & Goulias (2003), Sasaki & Nishii (2003), Srinivasan & Athuru (2004), Kenyon (2006), De Graaff & Rietveld (2007), Nobis & Lenz (2007), Lee-Gosselin & Miranda-Moreno (2009), Nobis, & Lenz (2009), and Lyons (2009). To our knowledge, no previous study has looked in an integrated way at the possible effects of ICTs on travel through changes in the dispersal of activities and the resulting consequences (positive or negative) for greenhouse gas (GHG) production, while controlling for other factors. In particular, past studies that control for socio-demographic factors and/or the influence of the built environment, *do not* account for the possible presence of endogeneity between ICT take-up and travel¹. Controlling for both socio-demographics and the built environment, it is not hard to believe that a person who has a heavy daily agenda with a lack of time and a very active lifestyle may be more likely to have and use mobile phones, and to use motor-vehicles to reach activity locations over a wide area with a resulting high production of GHG emissions.² If ICT access or use is not considered as a potentially endogenous variable, one might find a “spurious” dependence of ICT access and/or use on travel patterns. Finally, few studies have used fully disaggregated data to estimate ICT impacts at the individual level.

This paper focuses on the potential role of access to two ICTs – mobile phones and home Internet connections – in the spatial dispersion of an individual’s out-of-home activities and

¹ Endogeneity may be present in statistical models owing to the correlation between ICT access or use and travel outcomes (e.g., car usage and GHGs).

² In other words, ICT can motivate travel and at the same time travel can motivate ICT access and use.

travel, and in her/his production of GHGs. We introduce a novel integrated approach that controls not only for socio-demographics, but also for differences in the built environment at the home location, represented by neighbourhood typologies. This is tested using a 7-day activity/travel diary with geocoded out-of-home activity locations, enabling measures of each respondent's spatial dispersion of activities and a GHG emissions inventory constructed from his/her trips. Socio-demographics and built environment factors are also taken into account, involving complementary sources of data. The approach combines a set of spatial analysis techniques and an advanced simultaneous modelling approach that takes potential self-selection effects into account.

2. LITERATURE REVIEW

There is a significant body of literature investigating different aspects of the complex relationship between ICTs (such as the Internet and mobile phones) and travel behaviour. This goes back to the seminal work of Salomon (1985), who introduced the four potential interactions of ICT and travel: substitution, modification, neutrality and the generation of travel. Empirical evidence has provided insights on these interactions. For example, contrary to the initial speculation that ICT would lead to the elimination or substitution of the need for some travel, the so-called information revolution has been accompanied by an increase or generation of additional travel, e.g., see Choo & Mokhtarian, 2007.

Moreover, other studies have provided some insights on how ICTs can lead to a more flexible organization of activities in time and space, and hence the generation of additional travel. Some examples are Kim & Goulias (2003), Bhat et al. (2003), Srinivasan & Raghavender (2006), Lenz & Nobis (2007), Kenyon & Lyons (2007), De Graaff & Rietveld (2007), Lee-Gosselin & Miranda-Moreno (2009), and Foss & Couclelis (2011). From these studies, the impact of mobile telephones seems to be different from the impact of the Internet on activity and travel patterns. Mobile phone use is sometimes associated with increased out-of-home activity participation and

travel. However, the effect of Internet is less clear and in some cases, it has been associated with reduced travel. The complexity of interactions between ICT and travel behaviour has required the introduction of new concepts such as activity fragmentation (Couclelis, 2000; Lenz & Nobis, 2007), multitasking (Kenyon & Lyons, 2007) and the balance between e-communication and travel (Foss & Couclelis 2011; Roy et al, 2011). An important body of research has also looked at teleworking and the size of net benefits from any changes in travel and emissions – e.g., see Koenig et al. (1996). Teleworking is, however, outside the scope of this paper.

From these developments, it is reasonable to infer that ICTs are connected to the dispersal of out-of-home activities, the predominant measure of which is known as “activity space”. The concept of activity space and its use to represent spatial behaviour draws on more than four decades of research in behavioural geography, and in recent years this has received a boost from increasingly accessible geocomputing tools. Buliung & Remmel (2008) and Buliung et al (2008) provide a literature review and an introduction to the software tools available. Among the examples of research from the past decade is Axhausen et al (2001), who provide evidence of behavioural dynamics from unusually long activity-travel diaries (the six week Mobidrive survey). Buliung & Kanaroglou (2006) examine the potential household activity-travel response to a planned metropolitan polycentric hierarchy of activity centers. Their empirical evidence indicates an urban/suburban differential, with less daily travel and smaller activity spaces for urban households. Along similar lines, Manaugh & El-Geneidy (2011) use centographic analysis to study the spatial dispersal of household activities. They explore the effect of accessibility measures, household size and socio-demographic factors. Among their results was that, while controlling for accessibility measures, wealthier households with high car access have more dispersed activity locations than poorer households. Harding et al (2012) examine the effect of clusters of land-use indicators on activity spaces while controlling for socio-demographics. Their results point to a significant relationship between activity dispersion and low levels of population

and employment density, low levels of public transit accessibility and land use mix. However, in the literature, the effects of ICT on the dispersion of activities have been reported only rarely. An exception is the recent work of Alexander et al. (2011) who studied activity dispersion in the context of the fragmentation of work-related activities. Their study found that ICT variables were associated with the fragmentation of work activities, in space and time.

Despite these important theoretical concepts and the accumulation of empirical evidence on ICT and travel behaviour, little research has been done on direct or indirect impacts on energy consumption and the environment – one can refer to Koenig et al. (1996), Fuchs (2008), and OECD (2010). Questions remain about the effects of the rapid adoption of ICTs on energy consumption, and therefore GHGs, at the individual, household or regional levels. Arguably, ICTs have contributed to major changes in the way we organize and execute activities and travel. With access to ICT, it is now possible to perform certain activities faster, in a more efficient and comfortable way, and at flexible times and places (such as organizing a spontaneous meeting with friends, e-commerce, e-work, online banking). It is plausible that these changes bring about decreases and/or increases in personal energy consumption and GHG production, but the net effects of these changes is unclear. From the environmental point of view, smaller activity spaces seem desirable since they represent opportunities for lower energy consumption and GHG production from motorized travel at the individual and household level. Although this seems logical, it has not been tested empirically, and we sought a new modelling approach for the purpose.

3. MODEL FORMULATION

Our working conceptualisation was thus that the spatial dispersion of activities performed, and GHGs produced, by a given individual depend not only on socio-demographics and land-use (neighbourhood) characteristics, but also on the accessibility of technological instruments such as ICTs, that facilitate the flexibility of activities.

The choice of whether or not a person owns and uses ICT is multi-faceted. It depends on various factors that can directly or indirectly affect both the ICT choice and travel outcomes that ICT use may engender. In this paper, we limit the notion of ICT choice to whether or not an individual has access to either or both of a mobile phone and a home Internet connection, rather than the level of ICT use. The following conceptual framework (**Figure 1**) illustrates the potential factors associated with access to mobile phone and Internet service for a given individual:

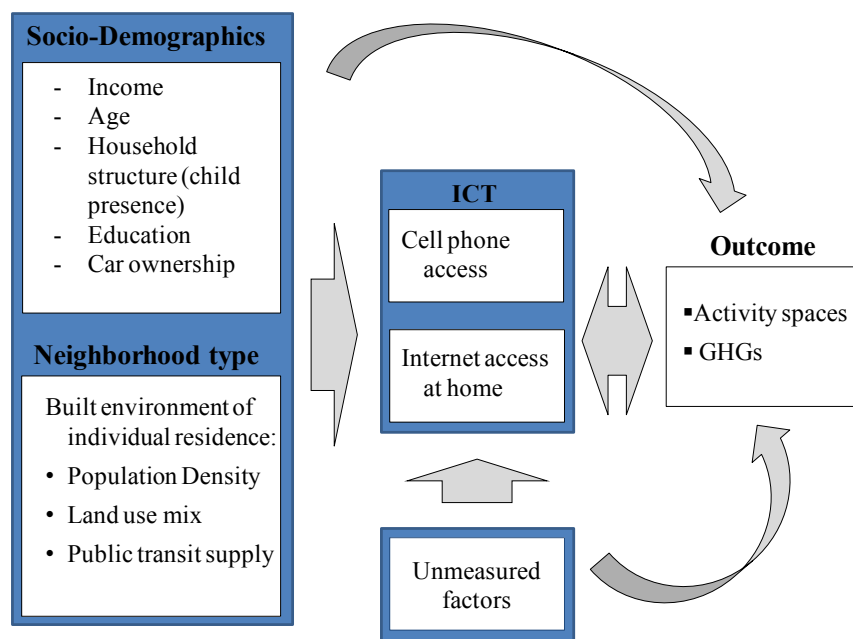


Figure 1. Conceptual framework – link between ICT and travel outcomes

In this framework, the choice of whether or not someone has access to a mobile phone and/or the Internet is directly affected by demographics. ICT access then directly influences the two travel outcomes: activity spaces and GHGs. The two travel outcomes, in addition to the ICT access, are affected in turn by socio-demographics and neighbourhood land-use characteristics. Moreover, unobserved factors that affect the individual's propensity to having ICT access are likely to affect his/her travel outcomes (activity spaces and GHGs) as well. For example, the social network of an individual might require him/her to be more connected through ICT access.

Furthermore, these individuals may be more likely to travel for longer distances to pursue joint activities with network members. The challenge, therefore, is to address the likely presence of endogeneity within the decision framework.

To estimate the effects of ICT access, an endogenous switching model is formulated adopting a similar approach to that proposed by Bhat & Eluru (2009). These authors estimated the impact of the built environment on daily household vehicle miles of travel (VMT), considering the self-selection effect of neighbourhood household location. In the current study, we hypothesise that an individuals' access to a mobile phone and Internet depends on his/her activity-travel desires and needs, socio-demographic profiles and unobserved personality traits. We assume that the unobserved individual factors are common to the travel behaviour outcomes (GHG and activity space). Hence, introducing ICT access as an independent variable in the travel outcome model does not adequately capture the relationship between ICT access and travel outcome. Further, the potential endogeneity will result in biased model estimation results.

To study the influence of ICT access on travel outcomes, taking into account the self-selection effect, the relationship is cast in the form of Roy's (1951) endogenous switching model system, which takes the following form (for details, see Maddala, 1983):

$$\begin{aligned}
 r_q^* &= \beta'x_q + \varepsilon_q, & r_q &= 1 \text{ if } r_q^* > 0, & r_q &= 0 \text{ if } r_q^* \leq 0, \\
 m_{q0}^* &= \alpha'z_q + \eta_q, & m_{q0} &= 1[r_q = 0]m_{q0}^* \\
 m_{q1}^* &= \gamma'w_q + \xi_q, & m_{q1} &= 1[r_q = 1]m_{q1}^*
 \end{aligned} \tag{1}$$

The first selection equation represents a binary discrete decision of an individual to have access to ICT (mobile phone or Internet). Note that this model however can be extended to the multinomial setting when modelling the different combinations of mobile phone and internet. As discussed above, due to the small sample size of the data used, this work models ICT only as a binary choice. The parameter, r_q^* in Equation (1) is the unobserved propensity to purchase

access to ICT relative to not having access to ICT, which is a function of an $(M \times 1)$ -column vector x_q of individual attributes (including a constant). β represents a corresponding $(M \times 1)$ -column vector of individual attribute effects on the unobserved propensity to employ ICT. In the usual structure of a binary choice model, the unobserved propensity r_q^* gets reflected in the actual observed choice r_q ($r_q = 1$ if the q th individual chooses to have access to ICT, and $r_q = 0$ if the q th individual decides not to use ICT). ε_q is standard logistic error term capturing the effects of unobserved factors.

The second and third equations of the system in Equation (1) represent the continuous outcome variables (such as activity space and GHGs) in our empirical context. μ_q is a latent variable representing the area or GHGs if a random individual q were to have ICT available, and ν_q is the corresponding variable if the individual q were to not have access to ICT. These are related to vectors of individual attributes z_q and w_q , respectively, in the usual linear regression fashion, with η_q and ξ_q being random error terms. Of course, we observe m_{q0}^* in the form of m_{q0} only if individual q in the sample is observed not to employ ICT. Similarly, we observe m_{q1}^* in the form of m_{q1} only if individual q in the sample is observed to have access to ICT. The potential dependence between the error pairs (ε_q, η_q) and (ε_q, ξ_q) has to be expressly recognized in the above system. In our study we employ the framework developed in Bhat and Eluru (2009) to accommodate for the potential dependence. For the sake of brevity, the copula framework³ that was employed is not elaborated here.

4. CASE STUDY

4.1 Initial steps

For model development, the following preparatory steps were taken:

³ The copula framework refers to coupling techniques of marginal error terms from various distributions through a pre-defined relationship. The copula approach allows for many flexible coupling options.

- *Data preparation:* An extract was made from a multi-day activity-based survey including out-of-home activities, travel characteristics and socio-demographics. Measures of activity spaces and GHG production were generated from these survey data.
- *Neighbourhood typology generation.* This was performed using a grid-based GIS approach and a k-means cluster analysis using supplementary data on three land-use variables: land use mix, population density, and public transit accessibility.

These two steps of data generation are explained further below.

4.2 Activity dispersion and GHGs

The primary data used in this study are from Quebec City, a provincial capital with a predominantly tertiary economic base and a slowly growing metropolitan area population in the region of 700,000. It has an unusually high penetration of limited access urban roads and a substantial urban bus network.⁴

The study data were collected in the period 2003 to 2004, during the first wave of the Quebec City Travel and Activity Panel Survey (QCTAPS), a three-wave panel survey that ended in 2006. This period is of a particular interest since the penetration of mobile phones and home-based Internet was at or approaching a majority of individuals. Canadian mobile phone penetration was at approximately 42% in 2003 while the Internet penetration (individuals with internet access at home) for the same year was at approximately 61%. Note that in the sample of individuals used in our analysis, the mobile phone penetration was 41.6% and that of internet penetration was 69.8%- which are not far from the mean national values for the same year.

⁴ In 2006, the north shore communities that had about 525,000 of the metropolitan Quebec City region's population had 178 Km of "autoroutes", or about 33 Km for per 100,000 inhabitants. By comparison, the whole island of Montréal had about 200 Km of "autoroutes" for about 1,855,000 people, or about 11 Km per 100,000 inhabitants.

The QCTAPS employed an unusually in-depth multi-instrument package known as OPFAST to investigate the decision processes employed by individuals and households to organise their activities in space and time. Part of the package was an activity/travel diary that covered 7 consecutive days in wave 1 and two days in waves 2 and 3. Although the wave 1 to wave 3 retention rate was high (67%), only the first wave has been used in this analysis. The 7-day diaries were kept by 400 respondents aged 16 years and over from 247 households, yielding observations on 15,353 activities that took place in 4,971 unique locations (including both out-of-home activity locations and the individual's residential location). Information was validated and augmented during a home interview following the diary week, including the geographical location of each activity, which was later geocoded using a geographic information system (GIS). As can be seen in **Figure 2**, the activity locations were largely centred in the Quebec City census metropolitan area (CMA), but extended to New Brunswick, Montreal, and to Lac Saint-Jean in the North.

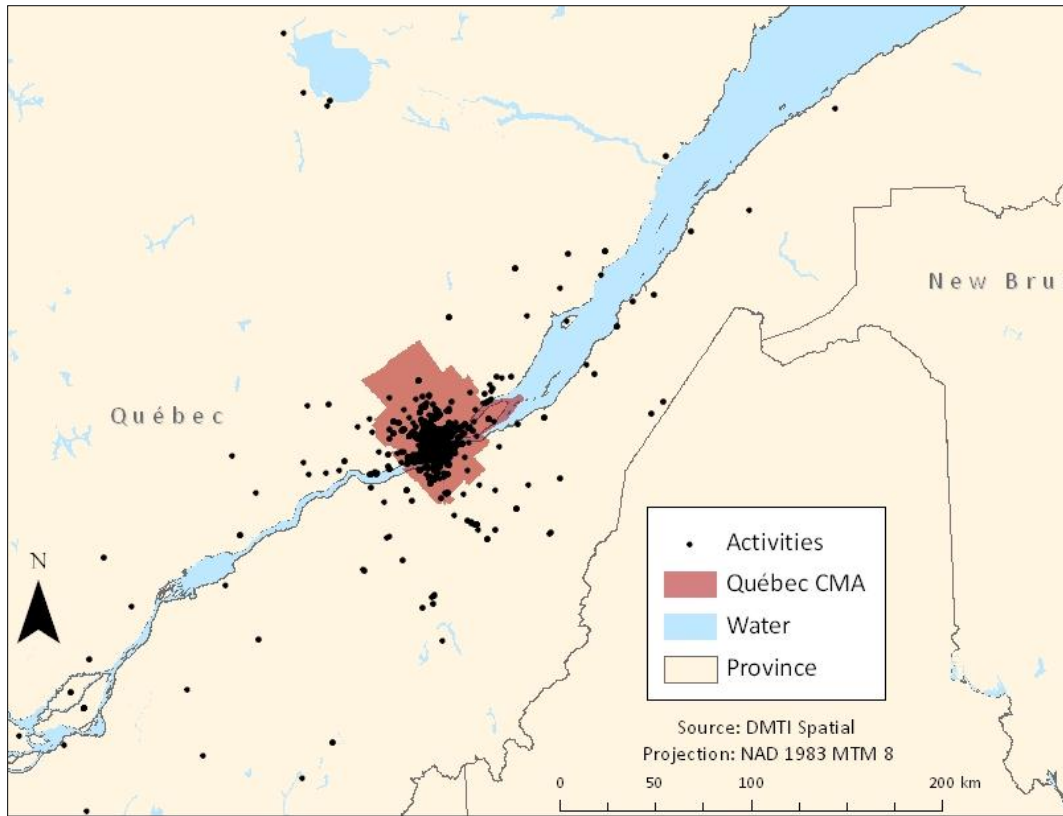


Figure 2: Location of activities in the Quebec City region

a) Activity space per individual - centographic analysis

A centographic analysis⁵ was undertaken to effectively measure certain characteristics of the activity spaces of the respondents to the survey, including the area or space covered during the development of the out-of-home activities of each individual. This analysis was performed in ESRI's ArcGIS using the directional distribution (standard deviational ellipse) tool, which creates an elliptical shape taking a given number of standard deviations based on the activities' geographical locations (Lee & Wong, 2001). In this case, an ellipse for each individual is generated at two standard deviations. As a first step, the standard deviation along the x axis (S_x) and y axis (S_y) are determined according to the form u_i as given in Eq. 2. The ellipse area is then determined based on

⁵ Centographic analysis refers to spatial statistical measures of central tendency and dispersion such as mean centre, standard deviational ellipse, elongation and orientation.

these standard deviations. To determine S_x and S_y , the angle of rotation (θ) is also needed. The result is one ellipse per respondent, generated using the out-of-home activity locations visited during a week. These measures are defined as:

$$Area = \pi S_x S_y, \quad (2)$$

Where:
$$S_x = \sqrt{2 \frac{\sum_{i=1}^n [(x_i - \bar{X}) \cos \theta - \sum_{i=1}^n (y_i - \bar{Y})^2 \sin \theta]^2}{n-2}}$$

$$S_y = \sqrt{2 \frac{\sum_{i=1}^n [(x_i - \bar{X}) \sin \theta - \sum_{i=1}^n (y_i - \bar{Y})^2 \cos \theta]^2}{n-2}}$$

$$\tan(\theta) = \frac{A+B}{C}$$

$$A = (\sum_{i=1}^n \tilde{x}_i^2 - \sum_{i=1}^n \tilde{y}_i^2)$$

$$B = \sqrt{(\sum_{i=1}^n \tilde{x}_i^2 - \sum_{i=1}^n \tilde{y}_i^2)^2 + 4(\sum_{i=1}^n \tilde{x}_i \tilde{y}_i)^2}$$

$$C = 2 \sum_{i=1}^n \tilde{x}_i \tilde{y}_i$$

With, \bar{Y} and \bar{X} represents the mean center for the activities. In addition, \tilde{x}_i and \tilde{y}_i are the deviations of the xy-coordinates from the mean center. Although other centographic measures can be generated such as the elongation and orientation of the ellipse (X/Y), as well as distances from the centroid of the ellipse to home and work or school anchor, for the purposes of this study, our primary interest is in activity space, for which the area of the ellipse is considered a simple and appropriate standardized representation. Moreover, other activity pattern measures can be used including shortest-path network measures and density of the activity locations - Schönfelder and Axhausen (2003). One could also calculate a polygon centroid, then measure dispersal with respect to such a point, but this has to be tested. Moreover, different geometries (shapes) have been tested such as the Cassini ovals, bean curves, polygons and super ellipses (Rai et al., 2007). However, none of the shape types is always the best activity-

space representation as recognized in Rai et al., (2007). The comparison of different measures and shapes is out of the scope of this work.

Figure 3 shows the ellipse for a particular respondent, overlaid on a map of the region. This visualisation of her/his activity space does not, of course, imply that the respondent visited all parts of the space encircled, nor that all of her/his activity locations are contained therein. Rather, it allows inter-respondent comparisons of size, shape, orientation and centroid.

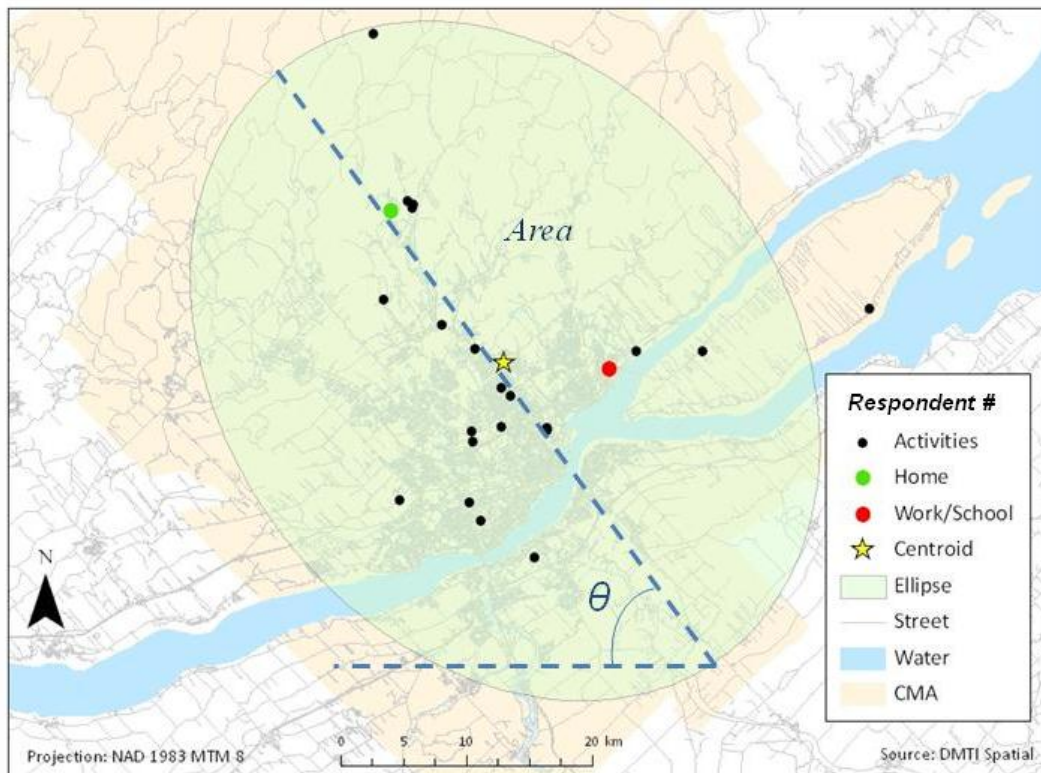


Figure 3. Ellipse representation for a given individual ⁶

b) GHG emissions per individual

GHGs were calculated for each individual trip using the methodology described in Barla et al. (2011). Emissions were computed taking into account distance, mode choice, vehicle characteristics (e.g., make, model and year), average trip speed and passenger occupancy (number of passengers in a given trip). Two emitting modes were distinguished, private motor

⁶ To respect confidentiality, the home location shown is intentionally imprecise.

vehicle (PV) and public bus (B). For the PV mode, the GHG emissions (in grams of CO₂ equivalent) generated for the respondent *i* in a given trip *t* are estimated as:

$$GHG^{PV}_{i,t} = [FCR_{i,t} \times SCF_t \times EF_{i,t} \times (D_{i,t}/100)] / NP_{i,t} \quad (3)$$

Where $FCR_{i,t}$ represents the average fuel consumption rate of the motor vehicle used in trip *t*, in liters per 100 km, and SCF_t represents the average speed correction factor⁷. D_t represents the estimated O-D distance in km for trip *i*. Distance was simulated using ArcGIS and the regional route network using shortest time trip. $EF_{i,t}$ is the emission factor. Type of fuel and the age of the vehicle were taken into account to obtain the emission factors reported by Environment Canada (2007). Finally, $NP_{i,t}$ corresponds to vehicle occupancy (or the number of passengers in the vehicle in each trip) excluding household children less than 16 years of age. For public bus, the GHG emissions are estimated using a similar approach. GHGs emissions at the trip level were then aggregated at the weekly individual level.⁸ Again, for additional details we refer to Barla et al. 2011. Summary statistics for the travel outcomes are provided at the beginning of the results section.

4.3 Neighbourhood typology

A neighbourhood typology was generated to represent built environment characteristics. The typology was developed according to the approach discussed in Miranda-Moreno et al. 2011, using population density, land use mix, and accessibility to public transportation, as the main built environment indicators. These variables were developed using a nine-cell grid method, which has been used in a number of projects that have proven the method a useful and efficient

⁷ Each trip was associated with an average speed according to the departure time (peak or off-peak period) and the origin and destination. The speeds and the fuel consumption correction factors were estimated by the Quebec Ministry of Transport (Barla et al. 2011).

⁸ Non-motorized trips were covered by the survey, but are treated as having zero GHG emissions.

way of representing neighbourhood types. This method has been found useful in that it avoids issues of processing time caused by buffer overlap, and allows the use of the same generated data for multiple projects, as the method is not based on any unit other than a grid across the area in question. Briefly, variables are generated at the grid cell level (with cells being defined as having a width and length of 500 meters each), and an observation (e.g. household) is given the attributes of the cell in which it lies as well as of the eight immediately surrounding cells.

The population density information was generated using data from the 2001 Canadian census. It was calculated as the number of people per area of residential use inside the nine-cell grid. Land use coverage data from DMTI Spatial was used for the development of a land use mix index and in the calculation of population density (area of residential development). Land use mix was based on the entropy index, which calculates the relative proportions of land uses in the nine-cell grid. Relevant land uses calculated in the index are residential, commercial, institutional and governmental, industrial and resource, and park or water. Bus lines and stops were obtained from the Réseau de transport de la capitale (RTC) and the Société de transport de Lévis, which were used in the calculation of public transportation accessibility. Public transit accessibility was created using an equation that incorporates the distance to the closest bus stop on each line passing through the nine-cell grid and the average daily headway of each of those lines. For more information on the neighbourhood typology analysis using the nine-cell grid technique, see Miranda-Moreno, et al. 2011.

Using these three variables (density, land use mix and transit accessibility), a k-means cluster analysis was used to generate five groups presented in **Figure 4. Table 1** gives a description of the five clusters with regard to the mean entropy index, population density (in persons/km²), and public transit accessibility. Note that each cluster has some particularities:

Cluster 1 - is characterized by the lowest values in all categories, which is also referred to as the periphery.

Cluster 2 & 3 are neighborhoods with low to medium density, land-use mix and transit accessibility. Most of these neighborhoods were built after the 60's. The observations (individual residential location) of these two clusters were grouped given the fact that cluster 3 has few observations, in addition to the fact that they have similar characteristics.

Cluster 4 represents neighborhoods with medium land-use mix and population density. This cluster also contains those neighborhoods that are served by the main transit lines (having moderated transit accessibility, similar to cluster 2). These neighborhoods are referred also as old suburbs since they were mostly built between the 1920s and the 1950s.

Cluster 5 – represents mostly the downtown core and central neighborhoods, with the highest values in each of the three input variables. This includes the historic core city, dating from the 17th century onwards, and a wide range of residential, commercial and industrial quarters built in the 18th to the 20th centuries.

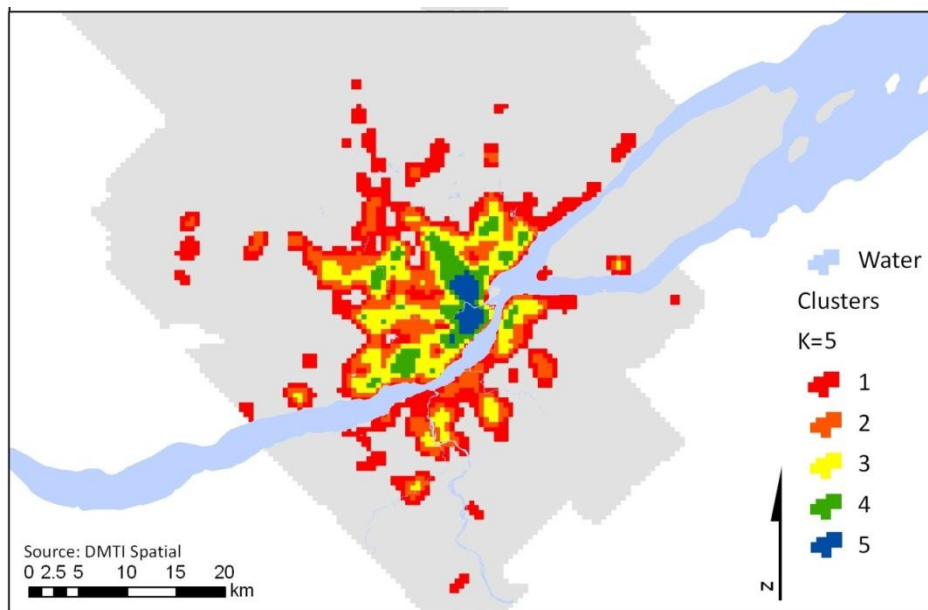


Figure 4. Neighbourhood typology

Table 1: Mean values for entropy, density, and accessibility per cluster group

Cluster	Entropy index ⁹	Population Density (persons/ km ²)	Public transit Accessibility
Cluster 1 (periphery)	0.20	498	7.4
Cluster 2 (new suburbs)	0.34	2,230	51.0
Cluster 3 (new suburbs)	0.39	4,097	88.4
Cluster 4 (old suburb)	0.43	6,622	83.9
Cluster 5 (downtown)	0.60	14,289	235.8

5. EMPIRICAL RESULTS

5.1 Exploratory data analysis

This section starts with an exploration of the variables involved in this study. **Table 2** presents summary statistics of travel outcomes including number of trips, total out-of-home activities, GHGs and ellipse area for individuals with and without access to a mobile phone, and with and without access to Internet. From these numbers, we can observe that the travel outcomes are higher for individuals who have access to mobile phone than for those who do not. In particular, important differences are observed for weekly GHG production and activity area, with a ratio of 1.3 (69.4/52.8kg) and 1.94 (3.7/1.9km²), respectively. For Internet access, a similar pattern is observed; however, the ratios are lower. This is without controlling for any other variables.

Summary statistics of the socio-economics at the individual and household level are presented in **Table 3**, and the distribution of the sample across the four neighbourhood types that were developed from the cluster analysis is also shown.

⁹ The entropy index varies between 0 and 1 (with 1 corresponding to a “perfect mix” and 0 to a homogenous area characterized by one sole land use).

Table 2. Statistics of travel outcomes at the individual level during 7-days (a week)

Travel outcomes (7 days)	Mean	Std. Dev.	Min	Max
<i>Without mobile phone</i>				
Number of trips in 7 days	26.6	10.3	4	73
Total activities in 7 days	34.1	15.4	4	95
Monday-Fri GHGs (kg)	40.9	37.0	0.0	263.2
Weekly GHGs (kg)	52.8	43.6	0.0	278.2
Total area (km ²)	1.9	6.4	6.0	57.1
<i>Individuals = 195</i>				
<i>With mobile phone</i>				
Number of trips in 7 days	29.0	10.2	7	55
Total activities in 7 days	38.9	15.4	10	86
Monday-Fri GHGs (kg)	62.9	53.8	0	308.5
Weekly GHGs (kg)	79.4	61.2	0	347.9
Total area (km ²)	3.7	27.9	18	330.4
<i>Individuals = 139</i>				
<i>Without Internet at home</i>				
Number of trips in 7 days	26.9	9.3	7	55
Total activities in 7 days	36.0	15.9	4	85
Monday-Fri GHGs (kg)	45.2	42.7	0	263.2
Weekly GHGs (kg)	58.4	50.0	0	278.2
Total area (km ²)	2.0	67.0	0.1	571.0
<i>Individuals = 121</i>				
<i>With Internet at home</i>				
Number of trips in 7 days	27.9	10.7	4	73
Total activities in 7 days	35.8	15.1	0	95
Monday-Fri GHGs (kg)	52.4	45.7	0	308.5
Weekly GHGs (kg)	66.2	52.5	0	347.9
Total area (km ²)	2.5	19.9	0.1	330.4
<i>Individuals = 279</i>				

Table 3. Sample Summary statistics

Variable group	Characteristics	Distribution of sample (%)
Individual Level	<i>Age (years)</i>	
	< 25	15.8
	25 to 50	47.2
	50 to 75	33.0
	Greater than 75	4.0
	<i>Gender</i>	
	Female	53.0
	Male	47.0
	<i>Employment Status</i>	
	Employed	56.5
	Student	8.8
	Retired	20.0
	Other	14.7
<i>Education</i>		
Bachelors or higher	30.5	
Education but less than Bachelors	41.5	
No education	28.0	
Household Level	<i>Household Size</i>	
	1	22.3
	2	37.5
	3	16.3
	4 or more	23.9
	<i>Household Children</i>	
	No children	59.8
	1	15.3
	2	13.5
	3 or more	11.4
	<i>Household Income (dollars)</i>	
	< 20,000	18.3
	20,001 to 60,000	48.0
	>60,000	30.3
	<i>Household car Ownership</i>	
0	9.4	
1	49.8	
2 and above	40.8	
Neighbourhood Typologies	Cluster 1 (Periphery)	21.1
	Cluster 2&3 (New suburbs)	34.8
	Cluster 4 (Old suburbs)	26.8
	Cluster 5 (Downtown)	17.3

5.2 Model selection

Based on the model formulation presented in equation 1, different copula model settings can be formulated. Specifically, 6 different copula structures were considered in this study: Gaussian, FGM, Frank, Gumbel, Clayton and Joe; for more details on these copulas, see Bhat & Eluru 2009. Note also that the model structure proposed is flexible enough to allow for the two copulas for each switching module to be different thus leading to 36 possible combinations. In this empirical analysis, we have two travel-related responses (activity space and GHGs) and two ICT choices (mobile phone and home Internet). For each travel outcome, an endogenous model system is formulated for each choice. For each of these systems, we empirically tested all 36 copula combinations. For the sake of brevity only the results of the best copula model are presented. It is also clear that ideally the choices should be examined as a four possible groupings of mobile and internet: 'with both mobile and internet', 'with mobile and without internet', 'without mobile and with internet' and 'without both mobile and internet'. However, modelling the 4 combinations would leave out some records that do not have cell phone information (66 records). By undertaking the estimation separately, it is possible to employ different samples for mobile (334 records) and internet (400 records). Given the small sample available for analysis, ICT choices are modelled independently.

For the selection of the best copula models, the Bayesian Information Criterion (or BIC) was used. The BIC for a given copula model is equal to $-2\ln(L) + K\ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence, K is the number of parameters, and Q is the number of observations. The copula that results in the lowest BIC value is the preferred copula. Note however that if all the competing models have the same exogenous variables and a single copula dependence parameter θ , the BIC information selection procedure measure is equivalent to selection based on the largest value of the log-likelihood function at convergence. Hence, in

our model estimation the log-likelihood measure can be used to determine the superior copula model.

The variable selection for the different models estimated in the study was based on a systematic process of examining the influence of the same universal set of variables. The universal set of variables included: (1) individual demographics (age, gender, respondent status, education level), (2) household demographics (household size, number of adults, presence and number of children, household income, household ownership, residence type -- such as detached home or apartment -- and car ownership), and (3) neighbourhood typology (represented by 5 clusters as defined previously, with cluster 2 and 3 being grouped in one cluster). The variables were selected based on intuitive reasonableness of the effect on the choice process as well as statistical significance. The sample size of the data used for analysis was smaller than in most applications and hence a less stringent statistical significance criterion was adopted i.e. if the variable impact was intuitively reasonable, the variable was retained for the universal set, even though the variable does not satisfy the usual significance criterion of p value <0.1 . Authors have also tested the specification to avoid multi-collinearity issues. The variance covariance matrix was also revised for the same purpose. Further, due to the smaller sample size, the coefficients in the linear equation (GHGs or activity area) are specified to be the same across the two linear regimes with the access indicator parameter, the scale parameter and the copula parameter accommodating the differences across regimes. This approach allows us to incorporate the influence of ICT access with fewer parameters.

5.3 Model results for mobile phone access

The upper part of **Table 4** presents the results for the choice to have a mobile phone available, estimated within a model of the natural logarithm of an individual's activity space (on the left), and a model of total GHGs (on the right). The lower part shows results for choice models of

activity space (on the left) and total GHGs (on the right), in both cases where an indicator of access to a mobile phone is included as an independent variable.

Table 4. Model results for mobile phone access

Component	Variables	Model for Activity Space			Model for GHGs		
		Estimates ^{***}	Std. Err.	p-value.	Estimates	Std. err.	p-value
Mobile phone access (<i>dummy variable, 0/1</i>)	constant 1	-0.53	0.38	0.17	-0.85	0.42	0.04
	Residential ownership	0.61	0.29	0.04	0.44	0.31	0.16
	Medium income [*]	0.35	0.30	0.24	0.68	0.32	0.04
	High income [*]	0.71	0.34	0.04	0.92	0.37	0.01
	Age	-0.02	0.01	0.03	-0.01	0.01	0.14
	Men	0.51	0.22	0.02	0.55	0.22	0.02
	No Diploma	-0.81	0.59	0.17	-0.89	0.77	0.25
Activity space (<i>columns 1 to 3</i>) or GHGs (<i>columns 4 to 6</i>)	Constant 2	20.14	0.52	0.00	0.45	0.10	0.00
	Car ownership	0.52	0.16	0.00	0.23	0.05	0.00
	Residential ownership	0.67	0.32	0.04	-	-	-
	Children present	-0.31	0.20	0.13	-	-	-
	Medium income	-0.25	0.26	0.34	-	-	-
	High income	-0.49	0.34	0.15	-	-	-
	Age	-0.02	0.01	0.03	-	-	-
	Men	0.21	0.19	0.26	0.08	0.05	0.15
	Employed	0.39	0.19	0.04	0.18	0.05	0.00
	Apartment	0.28	0.28	0.31	-	-	-
	Bac. degree or higher	0.27	0.19	0.15	0.07	0.05	0.16
	Cluster 2&3 ^{**}	-0.30	0.23	0.20	-0.18	0.06	0.00
	Cluster 4	-0.34	0.24	0.15	-0.29	0.08	0.00
	Cluster 5	-0.44	0.31	0.16	-0.32	0.09	0.00
Mobile phone access indicator	0.27	0.41	0.51	0.25	0.12	0.04	
Copula		Clayton			Frank		
copula parameter 1	rho1	1.65	1.02	0.11	4.32	1.39	0.00
copula parameter 2	rho2	1.13	0.54	0.04	3.93	1.79	0.03
scale parameter 1	sig1	1.56	0.15	0.00	0.40	0.02	0.00
scale parameter 2	sig2	1.40	0.10	0.00	0.59	0.05	0.00

* Reference category: low income; ** reference category: cluster 1, *** Parameters in bold are statistically significant at the 95% level.

Mobile phone access (0 or 1): In the activity space model, socio-demographics that were associated with access to mobile phones included: residential ownership, high household income, age and gender (with p-values less than 5%). From the results shown in the upper part of **Table 4**, the coefficients for males (0.51) and for higher income households (0.71) indicate that respondents with these characteristics were more likely to have a mobile phone available. But older individuals (coefficient of -0.02) were less likely to have access to a mobile phone. Residential ownership (coefficient of 0.61), a surrogate for social standing, may also be associated with mobile phone access. For the GHGs model, income categories and being men were the only factors statistically and positively associated with mobile phone access choice. The variable “no diploma” was found not statistically significant at the 10% level in both models,

Activity area component: After accounting for the unobserved influence of mobile phone access on the activity space component, individual socio-demographics, car ownership, and residential neighbourhood attributes were directly associated with activity space. Car ownership (0.52), as expected, was associated with a larger activity space, as was being employed (0.39), or owning one’s home (0.67). These variables were all statistically significant at the 5% significance level. The results also imply that individuals’ areas of activities diminish with age (-0.02). Being male or having a university degree shows only an indicative positive association with activity space (these variables were not statistically significant at the 0.10 level).

There is some indication that individuals from high and medium income households may have smaller activity spaces than households with lower incomes. Individuals living in apartment units had larger activity spaces than individuals from other residential types, yet individuals from *clusters 4* and *5* are likely to cover a smaller area than *cluster 1*. However, note that the p-values of these associations are up to 0.20.

GHG component: Compared to the activity space model, few socio-demographic variables turned out to be statistically associated with GHGs. Positive and statistically significant associations included car ownership (0.23), and employed (0.18). Unlike the activity space model, the neighbourhood *clusters 2 to 5* have a negative and statistically significant effect on the GHGs with respect to the reference cluster (*cluster 1* – periphery). From the cluster parameters, one can observe that the closer to downtown, the lower the GHGs.

Mobile phone effect on activity space and GHGs: Finally, the parameter “mobile phone access indicator” clearly highlights that individuals with a mobile phone available are likely to have a larger GHGs than individuals who do not, with a statistically significant effect at the 0.05 level. The same result was obtained for the activity space model - individuals with a mobile phone available were likely to have larger activity spaces compared to individuals who did not. However, in this model, the effect is not significant. Note also that the copula parameters in both models are statistically significant, clearly supporting the influence of common unobserved factors on both mobile phone access and the two travel-related outcomes, activity space and GHGs. Further, the non-significance of the “mobile phone” variable in the activity space model implies only that there is no mean observed effect of mobile phone on activity space. However, the significance of one copula parameter (0.04) and marginal significance (0.11) of the other copula parameter implies that the unobserved factors affecting mobile phone ownership also influence the dimension of activity spaces. This confirms the existence of endogeneity in the decision process.

5.4 Model results for Internet access

Table 5 uses the same layout as **Table 4** to show the results for access to the Internet at home. Thus, top left is the estimation of Internet access choice within the activity space model, and top right within the GHG model. Similarly, bottom left shows results for a choice model of activity

space, and bottom right a choice model of total GHGs, where an indicator of access to the Internet is included as an independent variable.

Internet access (0/1): The list of variables that affect access at home to the Internet is similar to that identified in the “mobile phone access” model. For the activity space model, variables positively associated with Internet access were residential ownership (0.81), presence of children (1.05), the number of adults within the household (0.48), age (-0.03), being male (0.21), higher education (0.78) and no diploma (-1.11) - all of them being statistically significant, except gender. For the GHGs model, very similar results were obtained, with the exception that number of household adults was also not statistically significant.

Activity area component: Most socio-demographic variables showed similar effects to those discussed above in the model that included an indicator of mobile phone access. These variables included a positive association with the area of an individual’s activity space for car ownership, being male, being employed and or living in an apartment. (some variables such as home ownership, living in a detached house or having a university education are not statistically significant). The principal negative associations were with the presence of children (-0.59) and age (-0.01), both being statistically significant.

GHG component: The socio-demographic variables across the GHG component are very similar to those in the “mobile phone” models in **Table 4**. Variables that appear in both travel-related models are car ownership, gender, and being employed. Other variables such as the presence of children and education do not have significant effects.

Table 5. Internet access results

Model components	Variables	Model for Activity Space			Model for GHGs		
		Estimates *	Std. err.	Sig.	Estimates	Std. err.	sig.
Internet access <i>(dummy variable, 0/1)</i>	Constant 1	0.43	0.50	0.39	0.78	0.43	0.07
	Residential ownership	0.81	0.34	0.02	0.71	0.31	0.02
	Children present	1.05	0.31	0.00	1.02	0.28	0.00
	No of household adults	0.48	0.25	0.05	0.22	0.25	0.37
	Age	-0.03	0.01	0.00	-0.03	0.01	0.00
	Men	0.21	0.25	0.41	0.22	0.23	0.35
	Bac. degree or higher	0.78	0.31	0.01	0.75	0.27	0.00
	No Diploma	-1.11	0.54	0.04			
Activity space <i>(columns 1 to 3)</i> or GHGs <i>(columns 4 to 6)</i>	Constant 2	19.63	0.68	0.00	0.64	0.11	0.00
	Car ownership	0.45	0.16	0.00	0.23	0.05	0.00
	Residential ownership	0.44	0.30	0.14	-	-	-
	Children present	-0.59	0.22	0.01	-0.06	0.06	0.36
	Age	-0.01	0.01	0.09	-	-	-
	Men	0.29	0.16	0.07	0.08	0.05	0.11
	Employed	0.37	0.17	0.03	0.20	0.05	0.00
	Detached home type	0.26	0.24	0.28	-	-	-
	Apartment type	0.45	0.27	0.10	-	-	-
	Bac. degree or higher	0.21	0.18	0.25	0.04	0.05	0.44
	Cluster 2&3	-0.27	0.23	0.24	-0.20	0.06	0.00
	Cluster 4	-0.16	0.23	0.49	-0.30	0.07	0.00
	Cluster 5	-0.47	0.27	0.09	-0.33	0.09	0.00
Internet access indicator	-0.18	0.57	0.76	-0.11	0.11	0.29	
copula parameter 1	rho1	1.29	1.67	0.44	3.87	1.49	0.01
copula parameter 2	rho2	2.01	1.88	0.28	4.84	1.59	0.00
scale parameter 1	sig1	1.52	0.14	0.00	0.48	0.03	0.00
scale parameter 2	sig2	1.42	0.06	0.00	0.46	0.02	0.00

* Reference category: low income; ** reference category: cluster 1, *** Parameters in bold are statistically significant at the 90%.

Internet effect on activity space and GHGs: Contrary to those with mobile phones available in the previous section, those with Internet at home have smaller activity spaces (ellipses) and GHGs. As noted above, this is consistent with the results obtained in some previous research. These effects are denoted by the negative coefficients on the Internet access indicator in both travel outcomes. Note however that these effects show only an indicative association (with large standard errors) and probably a larger data sample is necessary to confirm this finding. In addition, the copula parameters in GHG model are significant while the corresponding parameters in the activity space model are non-significant. The findings provide evidence of endogeneity between the internet presence and travel indicators, in particular for GHGs. However, analysis based on a larger sample is essential to confirm these findings.

5.5 Potential effect of ICT penetration

The potential impact of ICT access on activity space and GHGs is evaluated using the parameter estimates of switching models. The expected gains/losses (*i.e.*, increase or decrease in GHGs) are evaluated with a change in ICT access. For this purpose, we apply four measures that Bhat & Eluru (2009) proposed to study the potential influence of treatments:

- (1) Average effect of ICT (Average Treatment Effect (ATE)): this provides the expected travel outcome change for a random individual if s/he were to have access to ICT versus not having access to ICT.
- (2) Average impact of ICT access on those who have it (Treatment on the Treated (TT)): the TT measure captures the expected travel outcome change for an individual with ICT available, if s/he instead did not have access to ICT.
- (3) Average impact of ICT access on those who do not have it (Treatment on the Non-Treated (TNT)): this measure assesses the expected TB change for an individual picked from among those without access to ICT, and placed in a pool of those with ICT available.
- (4) Average impact of ICT on those with and without ICT access (Treatment on the Treated and Non-Treated(TTNT)): this measure combines the TT and TNT

measures into a single measure that represents the average impact of ICT on individuals who currently have access to ITC, and on those who currently have none.

Table 6: ICT Effects for Independent model and Best Copula model

Model structure	Model	Average effect of ICT (ATE)	Ave. effect on those with access (TT)	Ave. effect on those without access (TNT)	Average impact on those with and without access (TTNT)
ICT effects for Best Copula model**	Mobile phone impacting Activity Area	2.81	14.89	10.50	12.32
	Mobile phone impacting GHGs	39.02	27.55	30.95	29.54
	Internet impacting Activity Area	-25.21	-25.49	-22.27	-24.52
	Internet impacting GHGs	-17.70	-18.60	-20.35	-19.13
ICT effects for an independent model that fails to take account of endogeneity**	Mobile phone impacting Activity Area	-1.12	-1.34	-0.96	-1.12
	Mobile phone impacting GHGs	-1.56	-1.66	-1.67	-1.67
	Internet impacting Activity Area	-16.97	-17.36	-14.99	-16.65
	Internet impacting GHGs	-1.57	-1.67	-1.67	-1.67

** In terms of % change with respect to the mean

The results of this sensitivity analysis are presented in **Table 6**. From these results, one can observe the impact of using the inappropriate model (independent model without accounting for endogeneity) and the hypothetical or potential effect of ITC on the studied travel outcomes.

Potential effect of mobile phone access: Examining the impact of mobile phone access on activity space and GHG outcomes, the results clearly illustrate that access to mobile phone associates with an increased activity space for individuals. In fact, a 100% rate of mobile phone access would be accompanied by an increase in activity space by

12.3% (TTNT). The potential implications for GHG emissions are more important. In this model, we see that a hypothetical saturation of mobile phone access would be associated with an increase of 29.5% in GHG emissions. With the increasing take-up of mobile phone services in Canada, this could be cause for concern. The results also clearly highlight the difference between the independent model and the copula model. It is also important to mention that the failure to take endogeneity into account would change the sign on the results.

Potential effect of Internet access: The corresponding results for Internet access show an opposite trend to those from the mobile phone access model. Thus, according to these models, increased access to Internet would be associated with a reduction in activity space (-24.5%) and in GHG emissions (-19.1%). The results indicate that this effect, however, is not as pronounced as the (positive) associations with mobile phone access. Again, even in this case, the difference between the copula model and the independent models is very large, clearly indicating the presence of common unobserved factors affecting the choice process.

6. CONCLUSION

This paper presents an original methodology for evaluating the impact of ICT access (Internet and mobile phone) on two important mobility-related measures: activity spaces and weekly GHGs at the individual level. The proposed methodology was implemented on data from a diary survey of the activities and travel of respondents during a 7-day period. As a first step, respondent activity spaces were generated using a centographic measure of the spatial dispersion of out-of-home activity locations. Secondly, individual production of GHGs from motorized travel was estimated as a function of travel distance, average trip speed, vehicle characteristics and vehicle occupancy for both household passenger vehicles and transit.

Thirdly, a neighbourhood typology was generated to represent land-use characteristics based on three indexes: population density, land use mix and transit accessibility. As a final step, an endogenous switching model was used to deal with the correlation between the ICT choices and travel outcomes (endogeneity).

The principal findings from this study include:

- Socio-demographics have an important role in both ICT access and the two travel outcomes. Among the important factors affecting access to personal mobile phone and home-based Internet are gender, age, income and educational level.
- Not only socio-demographic factors, but also land-use neighbourhood typologies had a significant impact on both the size of activity spaces and GHGs. After controlling for other factors (including access to ICTs), residents of neighbourhoods with low population density and limited land use mix (Cluster 1) produced more emissions than those in the centrally-located Clusters 4 and 5.
- Model results show that mobile phone access was associated with increases in both personal activity spaces and GHGs, after controlling for built environment (neighbourhood typologies) and socio-demographics. From this study, it is estimated that those with a mobile phone available frequented activity spaces that were 12.3% larger, and produced 27.6% more GHG, than those with none, which is consistent with the positive impact of mobile phones on travel demand that has been identified in previous studies.
- Conversely, individuals with Internet access at home exploited smaller activity spaces (-24.5%) and produced lower GHG emissions (-19.1%). This result is also similar to past studies that have reported a negative impact of Internet access and use on travel distance or trip/activity frequency.

- This study shows the importance of using an appropriate model structure. The use of an incorrect model can lead to incorrect inferences.

The disaggregate approach to controlling for socio-economic factors and differences in the built environment, in combination with recent modelling techniques, yielded promising and plausible results using a relatively small sample in this study (about 400 individuals). In future work, it should be tested using a larger sample size. In addition to the small sample size, this study was limited to ICT *access*. The effect of ICT *usage* (e.g., hours using the Internet, or number of mobile phone calls) should also be explored. Moreover, a longitudinal study (survey with repeated measures over time for same individuals) would be ideal to measure the effect before and after a change in ICT access and usage, and as ICT access approaches saturation, more nuanced measures of usage, such as duration and type of communication, will become increasingly important. A larger sample size will be needed to examine the four possible groupings of the ICT choices (with and without mobile and/or internet). It is also important to note that ICT is not the only technological instrument that is a candidate for endogenisation. Car ownership is of particular interest for future development of this modelling approach as automobiles, like ICTs, facilitate the spatial and temporal flexibility of activities. Also, a comparative analysis of different activity dispersion measures and activity space shapes should be conducted to validate the sensitivity of the results to the measure used. The influence of ICT on various out-of-home activity types could be also explored.

Although this study was of limited scale, the results are of particular interest because they were drawn from a region at a juncture when mobile phone and Internet had recently crossed the threshold of 40% and 60% penetration in Canada, respectively. In more recent statistics, more than three-quarters (78%) of Canadian households reported they had a cell phone in 2010.

However, Quebec had the lowest rate of cell phone use at 69% of households for this year. .
This means that there is still an important proportion of the population without cell phones.

Finally, the results suggest that access to mobile phones and Internet may have substantial but opposite effects on the spatial dispersion of individual activities, and on the personal production of greenhouse gases. These effects are undetected when using model structures that do not address the likelihood that unobserved factors affecting the individual's propensity to have access to ICTs are also likely to affect his/her travel outcomes.

References

- Alexander, B., D. Ettema, et al. (2010). Fragmentation of work activity as a multi-dimensional construct and its association with ICT, employment and socio-demographic characteristics. *Journal of Transport Geography* 18(1), pp. 55-64.
- Axhausen K.W., D.M. Scott, A. König und. C. Jürgens (2001) Locations, commitments and activity spaces, paper presented at Survive Workshop, Bonn, December 2001, *Arbeitsbericht Verkehrs- und Raumplanung*, 96, IVT, ETH Zürich.
- Barla P., L.F. Miranda-Moreno, M. Lee-Gosselin (2011), Urban Travel CO2 Emissions and Land Use : A Case Study for Quebec City, *Transportation Research: Part D*, (16), 423-428.
- Bhat, C.R., Sivakumar, A. and Axhausen, K.W. (2003), An Analysis of the Impact of Information and Communication Technologies on Non-Maintenance Shopping Activities, *Transportation Research: Part B*, (37), 857-881.
- Bhat C.B., Eluru N. (2009), A copula-based approach to accommodate residential self-selection effects in travel behavior modeling. *Transportation Research: Part B*, (43), 749-765.
- Buliung, R. N. and P. S. Kanaroglou. 2006. Urban form and household activity-travel behaviour. *Growth and Change* 37, pp. 174-201.
- Buliung RN, TK Rimmel (2008) Spatial analysis, open source and activity-travel behaviour research: Home-rang and centographic estimation capabilities of the *aspace* package. *Journal of Geographical Systems*, 10 pp. 191–216.
- Buliung RN, Roorda MJ, Rimmel TK (2008). Exploring spatial variety in patterns of activity-travel behaviour: initial results from the Toronto Travel-Activity Panel Survey (TTAPS). *Transportation*, 35(6), pp. 697-722
- Choo S. and Mokhtarian, P. L. (2007), Telecommunications and travel demand and supply: Aggregate structural equation models for the US. *Transportation Research: Part A*, (41), 4-18.
- Couclelis, H. (2000) From sustainable transportation to sustainable accessibility: Can we avoid a new tragedy of the commons? In: Janelle, D. G. and Hodge, D. C. (eds): *Information, Place and Cyberspace*. Berlin: Springer, pp. 341–356.
- De Graaff T., Rietveld P. (2007), Substitution between working at home and out-of-home: The role of ICT and commuting costs, *Transportation Research: Part A*, (41), 142–160.
- Foss S.& Couclelis H. (2011), Throwing space back in: a tale of Indian fishermen, ICT and travel behaviour. *Journal of Transport Geography*, (17), 134–140.
- Fuchs C. (2008), The implications of new information and communication technologies for sustainability, *Environ Dev Sustain* (10), 291–309.
- Harding C., Patterson, Z., Miranda-Moreno, LF, Zahabi A., (2012). Modeling the effect of land use on activity spaces. Presented at the Transportation Research Board (TRB) 91st Annual Meeting, Washington D.C.

- Kenyon S. and Lyons G., (2007), Introducing multitasking to the study of travel and ICT: Examining its extent and assessing its potential importance. *Transportation Research: Part A*, (41), 161–175
- Kenyon, S., (2006), The ‘accessibility diary’: discussing a new methodological approach to understand the impact of Internet use upon personal travel and activity participation. *Journal of Transport Geography*, (14), 123–134.
- Kim T. and K. G. Goulias (2003), Cross sectional and longitudinal relationships among information and telecommunication technologies, daily time allocation to activity and travel, and modal split using structural equation modeling. *83rd Annual Transportation Research Board Meeting*, Washington, D.C., January 11-15, 2004.
- Koenig B.E., Henderson, D.K., Mokhtarian, P.L. (1996), The travel and emission impacts of telecommuting for the state of California Telecommuting, pilot Project. *Transportation Research: Part C*, (4), 13–32.
- Lee-Gosselin M. and Miranda-Moreno L. (2009), What is different about spontaneous urban activities that were planned with the aid of ICTs? Some early evidence from Québec, Canada, *Journal of Transport Geography*, (17), 104-114.
- Lee, J. Wong, D.W.S. (2001), *Statistical Analysis With ArcView GIS*, John Wiley & Sons, Inc.
- Lenz B. and Nobis C. (2007), The changing allocation of activities in space and time by the use of ICT-“Fragmentation” as a new concept and empirical results, *Transportation Research, Part A*, (41), 190-204.
- Lyons, G., (2009), The reshaping of activities and mobility through new technologies. *Journal of Transport Geography*, (17), 81–82.
- Maddala, G. S., (1983), *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press.
- Manaugh K. El-Geneidy, A (2011). What makes travel local? Defining and understanding local travel behaviour. World Symposium on Transport & Land Use Research (WSTLUR), Whistler, BC, Canada. *Journal of Transport and Land use* (accepted).
- Miranda-Moreno, L., Bettex, L., Zahabi A., Kreider, T., Barla P. (2011), A simultaneous modeling approach to evaluate the endogenous influence of urban form and public transit accessibility on distance travelled. *Transportation Research Record*, 2255, 100-109. .
- Mokhtarian P.L., and Salomon I. (1996), Modeling the choice of telecommunications: A case of the preferred impossible alternative, *Environment and Planning*, (28), 1859-1876.
- Mokhtarian, P. and Salomon, I. (2002), Emerging travel patterns: Do telecommunications make a difference? In: Mahmassani, H. (Ed) *In Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges*, Pergamon, Oxford, 143-182.
- Nobis C. and Lenz B. (2004), Changes in Transport Behavior by the Fragmentation of Activities. *Transportation Research Record*, No. 1894. 249-257.

- Nobis, C., Lenz, B. (2009), Communication and mobility behaviour – a trend and panel analysis of the correlation between mobile phone use and mobility. *Journal of Transport Geography*, (17), 93–103.
- OECD (2010), Greener and Smarter: ICTs, the Environment and Climate Change, Organisation for Economic Co-operation and Development (OECD), report (<http://www.oecd.org/dataoecd/27/12/45983022.pdf>).
- Rai, R.K., Balmer, M., Rieser, M., Vaze, V.S. Schönfelder, S., and Axhausen K.W. (2007) Capturing Human Activity Spaces, New Geometries. *Transportation Research Record*, 2021, 70–80.
- Roy, A. D., (1951), Some thoughts on the distribution of earnings. *Oxford Economic Papers*, New Series 3(2), 135-146.
- Roy P., Martínez, A.J., Miscione, G. Zuidgeest, M.H.P., van Maarseveen M.F.A.M. (2011), Using Social Network Analysis to profile people based on their e-communication and travel balance. *Journal of Transport Geography* (in press).
- Salomon, I. (1985), Telecommunications and Travel. *Journal of Transport Economics and Policy*, 19(3), pp.219-235.
- Sasaki, K., Nishii, K., (2003), Measurement of intention to travel: considering the effect of telecommunications on trips. *Transportation Research Part C: Emerging Technologies* 18, 36–44.
- Schönfelder, S., and Axhausen, K. W., (2003) Activity Spaces: Measures of Social Exclusion? *Transport Policy*, Vol. 10(4), 273–286.
- Srinivasan, K. and S. R. Athuru (2004), Modeling interaction between internet communication and travel activities: Evidence from Bay Area, California, Travel Survey 2000. *Journal of the Transportation Research Record*, 1894, 230-240.
- Srinivasan, K. Raghavender, P.N. (2006), Impact of mobile phones on travel: empirical analysis of activity-chaining, ride-sharing and virtual shopping. *Journal of the Transportation Research Board*, 1977, 258-267.
- Wang D. and Law F. (2007), Impacts of Information and Communication Technologies (ICT) on time use and travel behavior: a structural equations analysis. *Transportation*, 34(4), 513-527.

Acknowledgements

The work described in this paper was undertaken on data developed from 2000 to 2008 by the PROCESSUS Network. It was supported primarily by the Social Sciences and Humanities Research Council of Canada as the Major Collaborative Research Initiative *Access to activities and services in urban Canada: behavioural processes that condition equity and sustainability*, GEOIDE, the Canadian Network of Centres of Excellence in geomatics, and the Ministère des transports du Québec. This work was also partially financed by the *Fonds de recherche du Québec - Nature et technologies*, as part of the program *Recherche partenariat contribuant réduction et séquestration gaz effet de serre*. The authors would like to thank Pierre Rondier (Laval University), who built the relational database for the Québec City Travel and Activity Panel Survey as well as Philippe Barla (Laval University) for his invaluable assistance with the GHG estimation. The insightful suggestions by three anonymous reviewers for improvements to the paper were very appreciated.