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Trip generation of vulnerable populations in three Canadian cities: a spatial ordered probit approach

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Abstract This paper provides an analysis of trip generation of three vulnerable groups: single-parent families, low income households, and the elderly. It compares the mobility of these groups to that of the general population in three Canadian urban areas of Hamilton, Montreal and Toronto, based on data from large-sample metropolitan transport surveys. An ordered probit model with spatially expanded coefficients is used for the analysis. Spatial expansion shows that there are spatial mobility trends for elderly populations and low-income populations even after socio-economic attributes are accounted for. Such spatial differences are not generally found for single parent families. This novel spatial analysis provides clues as to where vulnerable populations may experience greater degrees of social exclusion. It provides information to help prioritize transportation infrastructure projects or other social programs to take into account the needs of vulnerable populations with the lowest levels of mobility.

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Introduction

Transportation systems and services are central to the livability of modern cities (Solomon 2000). This is evident to anyone who has experienced both the convenience of being able to regularly reach a variety of service and opportunity locations, or the nuisance of daily congestion in any major metropolitan area. For many, the advantages and disadvantages of transportation are fairly evident, and are a necessary aspect of urban living. For some others only the disadvantages are clear, a situation that can lead to a long string of unsatisfied needs. The quality of the transportation experience of various vulnerable population segments is a growing concern, given the (usually negative) presumed implications of poor mobility for full participation in the activities that satisfy the needs of daily life. These population segments include the poor, who may lack the means to realize their mobility potential, the old, who may face the onset of reduced ability and vigor to negotiate their environment, and individuals in single-parent households, who must undertake multiple vital roles as housekeepers and bread-earners. Transportation disparities (e.g. differential access to mobility tools and transport services and infrastructure) have been identified as important factors in the processes of social exclusion and environmental justice in the UK (e.g. Church et al. 2000; Social Exclusion Unit 2003; Lucas 2004; Kenyon et al. 2003), US (e.g. Bullard 2000; Giuliano 2005; Deka 2002; Scott and Horner 2008) in Canada (e.g. McCray and Brais 2007; Litman 2007), and in Australia (e.g. Currie 2009).

While initially motivated by issues of poverty and material deprivation, social inclusion/exclusion is now more broadly seen as a distinct concept. Todman (2004), for instance, argues that social exclusion shifts the focus away from economic poverty and material deprivation, to concentrate instead on the various other (e.g. social, political, and cultural) dimensions of being disadvantaged. Thus, whereas poverty is characterized as resource insufficiency, social exclusion is regarded as the inability to exercise rights, and while poverty is caused by unmet needs, social exclusion is a consequence of barriers to accessing social institutions (Abrahamson 2003). Despite the potential overlap between poverty issues and social exclusion, the distinction is important for several reasons. In poverty analysis, for instance, social stratification is vertical, with poor at the bottom and non-poor at the top. In contrast, from a social exclusion perspective, social stratification is horizontal, with those excluded on the outside or peripheral to the insider mainstream. After all, one needs not be poor to experience barriers that could affect full participation. The policy prescriptions are also different. Income generation through job and social welfare transfers directly addresses poverty, whereas enhancing access to opportunities is the preferred tool to decrease exclusion. This is not to say that material deprivation is not important. As Todman (2004) notes, increasing income is an important policy in social exclusion, however, increasing access to opportunities is central. The impact of an employment, education or recreational opportunity created would be diminished if it were not accessible to those it was supposed to benefit. A shift in attention towards improving *access* to opportunities means that mobility on the one hand, and the opportunity landscape on the other, should be central elements in social inclusion research (Social Exclusion Unit 2003; Lyons 2003; Lucas 2004; Miller 2006).

The objective of this paper is to contribute to the literature on the social exclusion dimension of transportation. There are a number of different perspectives from which mobility can be thought to affect the ability of individuals to fully participate in the activities of daily life. In this paper, we focus on the generation of trips, which is a general indicator of out-of-home activity engagement. Three Canadian urban areas for which detailed travel behavior information is available are analyzed, namely Hamilton, Montreal, and Toronto. Our choice of target population segments is dictated by current demographic trends in Canada. Cities in this country, partly fueled by immigration, have an increasing population of low-income residents whose job opportunities and other activity destinations are disconnected (Bourne 2003). Also motivating the study is the rapid aging of the Canadian population (Newbold et al. 2005; Scott et al. 2009). In Central Ontario, for example, the proportion of population older than 65 years of age is projected to escalate from 12 to 25% in 2021 (Bourne 2003). While higher levels of education, health, technology access, and auto dependence have characterized the aging baby boom generation (Bush 2003), there are continued concerns about their mobility needs in the future, since many live in relatively low accessibility suburban locations and are expected to "age in place". Access to different modes of transportation has been identified as a key factor in affecting the mobility of this vulnerable population segment, and while auto ownership appears to be a powerful mobility enabler, the challenges of driving cessation have also been highlighted by recent research (Páez et al. 2007; Mercado and Páez 2009). Finally, single parents are of interest. While not the explicit focus of previous research, single parent families are a significant and growing population group in urban centers of Canada. The proportion of families in Toronto, Montreal and Hamilton led by a single parent increased from 25% in 2001 to 26% in 2006 (Statistics Canada 2001, 2006). Compared to couple families whose median annual income was $70,400 (Canadian) in 2006, the median income of single parent families was only $33,000, with 28% having an income below $20,000 (Statistics Canada 2001, 2006). The parent in such households single-handedly carries a heavy burden of both child-rearing and providing for the household, and is thus in greater need of convenient access to opportunities.

Analysis in the paper is based on the two largest travel surveys in Canada, namely the Greater Toronto Transportation Tomorrow Survey and the Greater Montreal Area Travel Survey, for the latest years currently available (2001 for Toronto and 2003 for Montreal). This research focuses on the spatial characteristics of travel behavior. Church et al. (2000) argue that most transport researchers studying exclusionary transport issues in the UK have dwelled on a "categorical" approach (i.e. focus on social groups such as women, older people, unemployed) while paying little attention to the spatial characteristics of their travel to activities. These researchers note important policy questions regarding the extent to which resources should be allocated to particular social groups or to specific geographical areas. Accordingly, the objective of this paper is to investigate whether personal attributes interact with location to influence trip generation. In this way, this study bridges the gap between purely individual factors and geographical propinquity in the study of transport-related social exclusion (q.v. Miller 2006).

Specifically, three hypotheses are tested. First, we test the hypothesis that variables such as employment and mobility tools have less positive effects on trip generation for vulnerable groups than for the general population. Clearly, if no variations are detected in trip generation behavior, it would be reasonable to conclude that social inclusion is not affected by this dimension of mobility. Second, we investigate whether there are systematic variations in mobility over space that cannot be captured as a function of individual attributes, but that are better explained as contextual effects emerging from the interaction between location and personal characteristics. The underlying question is whether travel behavior varies over space for identical socio-economic and demographic profiles. For example, members of "vulnerable" groups, may turn out not to be very vulnerable in specific locations. Third, if such spatial variations exist, we test whether they are different for vulnerable groups than for the general population. The analysis makes use of ordered probit models (Zavoina and McElvey 1975; Train 2003) that contain our substantive knowledge about the process, and the introduction of spatially expanded coefficients to capture contextual effects (Casetti 1972; Fotheringham and Brunsdon 1999). This paper further illustrates the potential of spatial analytical approaches which have steadily gained recognition as valuable tools in the analysis of transportation systems (e.g. Miller 1999; Bhat and Zhao 2002; Páez and Scott 2004; Páez 2007).

The paper is organized as follows. The following section discusses some background considerations. This is followed with a description of the data that are used for the analysis. The ordered probit model is then described and model results are provided before the addition of spatially expanded coefficients. Then, the method of spatial expansion is described, spatially expanded coefficients are added and the results of the spatial model are discussed, as they pertain to the three hypotheses. Finally conclusions about the value of this modeling technique and the policy implications of the results are provided.

Background

Mobility-related social exclusion has been conceptualized in the literature as the inverse of access (Lyons 2003) or the consequence of reduced accessibility (Kenyon et al. 2003). Consider the following definition:

> Social exclusion is "[the] process by which people are prevented from participating in the economic, political and social life of the community because of reduced accessibility to opportunities, services and social networks, due in whole or in part to insufficient mobility in a society and environment built around the assumption of high mobility." (Kenyon et al. 2003)

This definition stresses that the primary role of mobility is to provide access. In this regard, it is possible to differentiate the lack of mobility as a factor (of social exclusion) while lack of access is the consequence. Thus, the denial of access could be the result of inadequate mobility. Two important questions arise. The first question looks at the root of the problem of mobility limitations: what are the factors that affect mobility (absence or lack of it)? Giuliano (2005), for example, has shown that transit use is decreasing among the poorest income groups in the US, and has noted attitudinal data to showing dissatisfaction with public transit as one of the major factors. Deka (2002) has identified that auto ownership is lowest among poor household and suggests mobility may be influenced by focusing on transit provision for these households. Litman (2007) identifies a broad range of factors for transportation planners to consider for equitable provision of mobility. The second question asks what are the accessibility implications of mobility outcomes given a surrounding opportunity landscape? McCray and Brais (2007), for example, demonstrates the use of GIS tools for examining spatial and temporal constraints that are faced by vulnerable groups, using low-income women in Quebec as a case study. Kenyon et al. (2003) examine the role of virtual accessibility, and suggest that it should be recognized as a social policy tool that complements the provision of physical mobility.

In this paper, the focus is on the first question, and the measure of mobility investigated is the generation of trips as a measure of out-of-home activity engagement. Trip generation is a precondition for accessibility: individuals who do not travel do not, for obvious reasons, have access to any activities that must be conducted away from the place of residence and that cannot be completed remotely (i.e. activities that lack extensibility as discussed by Miller 2006; also see Kenyon et al. 2003). The number of daily trips is a simple but informative and robust measure of social exclusion: people who travel generally do so to reach work, school, shopping, social, entertainment, recreation, or personal business activity locations. Even leisure driving could be seen as a different setting for recreational or social activities. Participation in each of these activities is an indicator of inclusion in social and economic networks. Not making trips, on the other hand, indicates that significant time is spent within the confines of one's home. It is important to note that for some people it may be possible to effectively participate in society and the economy with few trips, e.g., through the use of information and communication technology (ICT), or by receiving visitors or home deliveries. So far, however, the literature on ICT and travel behavior is inconclusive with regards to the degree that telecommunication substitutes travel (e.g. Mokhtarian 2009), and relatively little is known about the characteristics of travel for visiting and other forms of social contact (e.g. Habib et al. 2008; Farber and Páez 2009). For these reasons, trip generation is a useful general indicator of mobility and potential for participation.

As outlined above, the research aims to identify whether significant differences exist in mobility patterns between groups of interest and the mainstream of society. The results are not expected to be completely unambiguous. Low levels of mobility may indicate that individuals either: (1) prefer to stay home, in which case extra mobility may be a superfluous and even counterproductive objective; or (2) face mobility barriers that require intervention to facilitate full activity participation.

Selection of variables for the analysis is informed by previous travel behavior empirical research. For example, earlier studies have shown a negative relationship between age and mobility in general (Mercado and Páez 2009; McDougall 1998; Poon et al. 2005; Rosenbloom 1990; Benekohal et al. 1994; Chu 1994; Stradling et al. 2005), and with numbers of trips in particular (Schmocker et al. 2005; Páez et al. 2007; Roorda et al. 2008). Employment status and household structure have been shown in the past to significantly impact travel making patterns. For example, Vance and Iovanna (2007) highlight the impact of employment on travel behavior, finding that employment is associated with a lower probability of car use. Scott and Kanaroglou (2002) have found significant interactions between household heads in the process of activity generation. Availability of mobility tools (e.g. driver's license, vehicles, nearby transit, transit pass ownership) is also known to have positive effects on mobility (Stradling et al. 2005; Páez et al. 2007). The findings describing the relationship between income and trip frequency, on the other hand, have been mixed (Chu 1994; Schmocker et al. 2005; Smith and Sylvestre 2001). While an examination of median income of traffic analysis zones in Hamilton showed no significant effect on trip frequency (Páez et al. 2007), income at the household level has been found to have a significant positive effect on distance traveled (e.g. Vance and Iovanna 2007; Georggi and Pendyala 2001; Limtanakool et al. 2006). Conceptually, the variables can be arranged according to the different dimensions of social exclusion identified by Kenyon (2003), including the personal (e.g. age, marital status, etc.), economic (e.g. income, auto ownership, employment status), and living space (e.g. physical and social environment) dimensions. For the purpose of this study, and keeping in mind that we wish to adopt a general definition of mobility aligned with the social exclusion view, trip generation is the term used to indicate the number of trips made by an individual person, for all purposes, over a 24 h period, by all modes.

Data

Data for this study come from two large-sample cross-sectional origin-destination (OD) travel survey programs in the Greater Toronto and Hamilton Area (GTHA) and the Greater Montreal Area (GMA). The survey instruments, survey procedure and sampling are largely consistent between these two surveys, with only a few differences. This consistency allows for useful inter-urban comparisons to be made, and allows us to test the transferability of conclusions.

In particular, in both regions, the survey is a retrospective 24 h autumn weekday trip diary, collected via computer aided telephone interview for approximately 5.8% of all households in the GTHA and 4.7% in the GMA. Detailed information about the household, all household members and the trips made by all household members 11 years of age or older are collected (data are collected for children 5 years of age or older in Montreal, but these records are not included in the analysis in this paper). In the surveys, and in all of the analysis in this paper, trips are defined as one-way trips from origin to destination. X–Y coordinates of household location and trip ends are available, allowing for fully disaggregate spatial analysis. Both surveys collect information every 5 years. The most recent available data for the Cities of Toronto and Hamilton is for 2001, whereas Montreal data are available for the year 2003. Table 1 summarizes the number of survey responses, the sampling rate, mean trip generation rates (for all purposes) and characteristics of the population for each of the three cities.

Three data limitations are relevant for this analysis. First, the Toronto Area survey did not collect short non-motorized trips to locations other than work and school. Second, because of proxy reporting in both surveys (one household member answers on behalf of all household members), there is some under-reporting of the trips made by persons not interviewed directly. Finally, only the 2003 Montreal survey collects income information (total household income for 2002 in Canadian dollars). This variable could not be considered in the analysis for Toronto and Hamilton, therefore the mean income of the census tract is used as a proxy. In order to more accurately reflect household income, census tract statistics are stratified according to household type, and the mean income assigned to each specific household depends on its structure.

Methods and analysis

Ordered probit model for trip generation

The first analysis tests the hypothesis that the trip generation of vulnerable groups (elderly, low income and single parents) is more sensitive to variables such as employment and mobility tools than the general population.

Trip generation analysis has traditionally followed one of three methods: cross classification models, trip rate models (Institute of Transportation Engineers 2004), and multivariate regression models, usually at the zonal or household level of aggregation (Badoe and Chen 2004). Linear regression models, perhaps the state of practice in transportation modeling, have been developed in Canada at the person level with large datasets in

Table 1 Summary statistics

	Hamilton, 2001	Toronto, 2001	Montreal, 2003
Household sampling rate (%)	5.4	6.0	4.7
Sample person records	22,855	126,645	150,608
Mean trip generation rate	2.54	2.31	2.27
		Proportion of sample	
Age			
<20 (%)	14	12	14
20–35 (%)	23	28	26
36–50 (%)	28	28	30
51–64 (%)	17	16	19
65+ (%)	18	16	12
Household income ($Canadian)			
Refuse/don't know (%)	–	–	23
<20K (%)	–	–	10
20–40K (%)	–	–	20
40–60K (%)	–	–	18
60–80K (%)	–	–	12
80–100K (%)	–	–	7
>100K (%)	–	–	9
Household structure			
Single (%)	10	11	12
Couple (%)	26	22	39
Couple W/children (%)	26	23	15
Single parent (%)	3	3	3
Other (%)	36	42	31
Mobility tools			
Driver license (%)	76	71	74
Vehicle own[a] (%)	91	84	88
*Age 65+ (%)	15	12	9
*Low income (<$20K) (%)	–	–	6
*Single parent (%)	2	2	2
Transit within 500 m[b] (%)	2	5	3
*Age 65+ (%)	0	1	0
*Low income (<$20K) (%)	–	–	1
*Single parent (%)	0	0	0
Occupation			
Full time employment (%)	44	48	49
*Age 65+ (%)	1	1	0
*Low income (<$20K) (%)	–	–	2
*Single parent (%)	1	1	1
Part time employment (%)	11	10	5
*Age 65+ (%)	0	1	0

Table 1 continued

	Hamilton, 2001	Toronto, 2001	Montreal, 2003
		Proportion of sample	
*Low income (<$20K) (%)	–	–	1
*Single parent (%)	0	0	0
Student (%)	19	19	18
Free parking at work (%)	45	37	7
Density	Mean	Mean	Mean
Population density (1000/km^2)	1.645	4.276	2.819

[a] , * Indicates a combined variable. For example, in Hamilton, vehicle own indicates that 91% of the sample lives in a household that owns a vehicle. Vehicle own * Age 65+ indicates that 15% of the sample are older than 65 years and live in a household that owns a vehicle

[b] Transit within 500 m = 1 if a subway or commuter rail stop is within 500 m of the individual's household

multiple cities over multiple years, to investigate why changes in trip rates have been observed (e.g. Roorda et al. 2008). Although this approach has been shown to predict trips better in some empirical applications compared to alternative models (Badoe 2007), it also presents several conceptual and practical limitations. These include the lack of upper and lower limits to the predicted number of trips, which can lead to unrealistically high or negative trip generation predictions, and limited theoretical support from a behavioral perspective, lacking the random utility foundation of other approaches. In order of increasing sophistication (Badoe 2007), alternative modeling approaches include the truncated normal, Poisson, and negative binomial models. These are all probabilistic approaches that lack a clear link to behavioral theory. Given that one of the purposes of this research is to better understand travel behavior, such a link is considered to be important. Disaggregate frequency-based discrete choice models (e.g. Boarnet and Sarmiento 1998; Schmocker et al. 2005) address some of the shortcomings of linear regression and provide a connection to utility theory (Train 2003, pp. 163–167). Ordered probit/logit models are appropriate when the outcome variable is ordinal, as it is for number of trips. As discussed by Train (2003), individuals facing ordinal decision processes (i.e. should I make one more trip?), can be thought to associate utility U with alternative numbers of trips. Trip decisions are made by an individual as follows:

- If $U < \lambda_1$, then number of trips $T = 0$
- If $\lambda_1 < U < \lambda_2$, then $T = 1$
- If $\lambda_2 < U < \lambda_3$, then $T = 2$
- If $U < \lambda_3$, then $T \geq 3$

The utility of individual i is decomposed into the usual systematic and random components:

$$U_i = X_i\beta + \varepsilon_i \tag{1}$$

$\boldsymbol{X}_i$ is a vector of individual attributes, $\boldsymbol{\beta}$ is a set of coefficients to be estimated. The error term ε_i captures unobserved/ unobservable factors, measurement/ observational errors, and other idiosyncratic variations. An ordered probit model assumes that ε_i follows a standard normal distribution (see Ortúzar and Willumsen 2001). Utility U_i is used to derive expressions for the probability that an individual makes 0, 1, 2, or 3 or more trips, as follows (more classes can be added in a straightforward fashion):

$$\begin{aligned}\Pr(0 \cdot trips) &= \Pr(U_i < \lambda_1) \\ &= \Pr(X_i\beta + \varepsilon_i < \lambda_1) = \Pr(\varepsilon_i < \lambda_1 - X_i\beta)\end{aligned} \tag{2}$$

$$\begin{aligned}\Pr(1 \cdot trip) &= \Pr(\lambda_1 < U_i < \lambda_2) \\ &= \Pr(\lambda_1 < X_i\beta + \varepsilon_i < \lambda_2) = \Pr(\lambda_1 - X_i\beta < \varepsilon_i < \lambda_2 - X_i\beta) \\ &= \Pr(\varepsilon_i < \lambda_2 - X_i\beta) - \Pr(\varepsilon_i < \lambda_1 - X_i\beta)\end{aligned} \tag{3}$$

Table 2 shows the results of estimating ordered probit models of trip generation for Hamilton, Toronto and Montreal. As previously noted, income is not available for individual respondents in the datasets for Hamilton and Toronto, therefore mean census tract (CT) household income, stratified by household type, is used instead. Variables with low statistical significance coefficients ($p > 0.05$) have been removed from the models to ensure that model efficiency is not sacrificed (Greene 2002).

The goodness of fit of the models is evaluated with an overall goodness of fit statistic which is computed as follows (see Ben-Akiva and Lerman 1985):

$$\rho^2 = 1 - \frac{L(\beta)}{L(c)} \tag{4}$$

where $L(\beta)$ is the maximum log-likelihood value, and $L(c)$ is the value of the log likelihood when it includes only constants, that is, the log likelihood of the least informative model. To introduce a measure of parsimony, the statistic can be adjusted for model size by introducing the number of explanatory variables K beyond the constants as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\beta) - K}{L(c)} \tag{5}$$

As shown in Table 2, goodness of fit is fairly consistent across cities, with the best fit found in Toronto. The values obtained are in line with or better than others reported in the literature (e.g. Boarnet and Sarmiento 1998, Table 2; Badoe 2007, Table 6). The deviance can be used to compute the likelihood ratio statistic for nested models.

Overall, there are similar trip generation characteristics between Hamilton, Toronto and Montreal, with a few differences. Trip generation tends to decrease with age. In all cases, people 65 years and older have the lowest propensity to make trips, and ages <20 have the highest propensity to make trips. However the decrease is not entirely monotonic, since the age group 20–35 has negative coefficients in all three cities. Household structure shows more mixed results between urban centers. Couples make fewer trips per person than singles and in Toronto and Hamilton this difference is more pronounced than in Montreal. Couples with no children tend to make fewer trips per person than singles (possibly because couples can share household tasks, and have more opportunity for social activity in the home). Couples with children have greater trip making probabilities than couples with no children. In Montreal, singles with children have a higher trip making propensity than singles without children, but this difference is not observed in Toronto and Hamilton. Vehicle ownership and the availability of a driver license both have a clear positive effect on the trip making rate in all three cities. Furthermore, vehicle ownership has a much greater positive effect on the trip rate of the elderly, in fact almost cancelling the negative effect of old age. While this indicates that the difference in mobility is negligible between seniors with access to a vehicle and members of the reference group with access to a vehicle, the implication is that driving cessation is yet again an important consideration (see Páez et al.

Table 2 Ordered probit models

	Hamilton, 2001		Toronto, 2001		Montreal, 2003	
$L(\beta)$	−20992.303		−105709.815		−114030.088	
$L(c)$	−22931.483		−119332.053		−125299.787	
ρ^2	0.0846		0.1142		0.0899	
$\overline{\rho}^2$	0.0837		0.1140		0.0897	
Deviance (−2 * logL)	41984.605		211419.629		228060.176	
n	22837		126319		150608	
Variable	Estimate	*p* value	Estimate	*p* value	Estimate	*p* value
Constant	−0.1866	0.0021	0.0542	0.0030	0.4369	0.0000
Thresholds (for identification: threshold 1 = 0)						
λ_2	2.0615	0.0000	2.2270	0.0000	2.4106	0.0000
λ_3	2.8839	0.0000	3.0458	0.0000	3.2840	0.0000
λ_4	3.4694	0.0000	3.6066	0.0000	3.8679	0.0000
Age						
<20	0.1775	0.0000	0.3548	0.0000	0.0708	0.0000
20–35	−0.1176	0.0000	−0.1122	0.0000	−0.0351	0.0001
36–50	Reference		Reference		Reference	
51–64	−0.0449	0.0404	−0.0733	0.0000	−0.0806	0.0000
65+	−0.3734	0.0000	−0.5230	0.0000	−0.4906	0.0000
Income						
Income (CT average)	0.0856	0.0001	0.0220	0.0000	–	
Income^2 (CT average)	−0.0048	0.0004	−0.0003	0.0000	–	
Refuse/don't know	–		–		−0.4066	0.0000
<20K	–		–		−0.2007	0.0000
20–40K	–		–		−0.1980	0.0000
40–60K	–		–		−0.1407	0.0000
60–80K	–		–		−0.0886	0.0000
80–100K	–		–		−0.0567	0.0001
>100K	–		–		Reference	
Household structure						
Single	Reference		Reference		Reference	
Couple	−0.2961	0.0000	−0.2410	0.0000	−0.0890	0.0000
Couple W/children	−0.1080	0.0106	−0.1391	0.0000	–	
Single parent	–		–		0.1544	0.0000
Other	−0.4179	0.0000	−0.4009	0.0000	−0.2126	0.0000
Mobility tools						
Driver license	0.4728	0.0000	0.5214	0.0000	0.3842	0.0000
Vehicle own	0.3286	0.0000	0.2075	0.0000	0.0999	0.0000
*Age 65+	0.3102	0.0000	0.3840	0.0000	0.3111	0.0000
*Low income	–		–		−0.1032	0.0000
*Single parent	0.2684	0.0004	0.1314	0.0001	–	

Table 2 continued

	Hamilton, 2001		Toronto, 2001		Montreal, 2003	
Variable	Estimate	p value	Estimate	p value	Estimate	p value
Transit Within 500 m			−0.0660	0.0001	0.0431	0.0276
*Age 65+	−0.4306	0.0006	0.1438	0.0014	0.1554	0.0022
*Low income	–		–		0.0874	0.0352
Occupation						
Full time employment	0.6586	0.0000	0.7792	0.0000	0.6468	0.0000
*Single parent	0.2007	0.0316	0.1371	0.0006	0.1317	0.0008
Part time employment	0.5213	0.0000	0.5025	0.0000	0.6139	0.0000
*Age 65+	–		0.2410	0.0000	0.1638	0.0103
*Single parent	−0.3042	0.0161	–		–	
Student	0.4465	0.0000	0.4957	0.0000	0.6561	0.0000
Free parking at work	–		0.0485	0.0000	0.3358	0.0000
Urban form						
Population density	–		−0.0144	0.0000	0.0143	0.0000

2007). In essence, losing access to a vehicle amounts to becoming old from a mobility perspective. Likewise, for single parent households, there is an additional positive effect to be had from vehicle ownership in Hamilton and Toronto, but not in Montreal. This effect is smaller but significant, and is suggestive of potential limitations faced by non-vehicle owning single parent households. Compared with vehicle ownership, the effect of proximity to transit (distance <500 m) has a small effect on trip generation, and is in fact negative in Toronto. It is important to note here that in the travel survey for Hamilton and Toronto, walk and bicycle trips to non-work/non-school activities are not collected, which may account for some of this difference (since high transit areas are generally more "walkable" as well). Also, the results suggest the importance of transit for elderly mobility; their trip rates increase with access to transit more than the rest of the population in both Toronto and Montreal. This is not true for single parents to a significant degree. The last common variable, population density, displays rather mixed results, since the impact is significant and negative in Toronto, significant and positive in Montreal, and not significant in Hamilton.

With regards to income, this is a variable that can only be evaluated in detail for Montreal because the travel survey in Toronto and Hamilton does not ask a question about income. To proxy for individual income in Hamilton and Toronto, the average census tract income has been included instead. Income turns out to be significant and therefore relevant whether it is measured at the level of individual households, or approximated by CT average values. In these three cities, income positively affects the propensity to make trips. In both Hamilton and Toronto the squared income term has a negative coefficient, indicating that the relationship is non-linear, a trend that can also be found by examining income ranges in Montreal.

Overall, the analysis reported in this section reveals some important differences in the trip generation behavior of the target population segments and the general population, thus lending convincing support to the first hypothesis set for the paper. The patterns uncovered are indicative (whether due to preference or otherwise) of reduced trip making by seniors and low income individuals, but not by individuals in single parent households. The results also provide evidence of the importance of access to mobility tools and employment status.

Geographical analysis

The second and third hypotheses examined in this paper are related to the variations of mobility over space and whether these variations are different for vulnerable groups than for the general population. These hypotheses are tested by undertaking a geographic analysis. A few methods have been used before to describe spatial variation, including multi-level approaches (Bhat and Zhao 2002; Páez et al. 2007) and geographically weighted regression (GWR) models (Fotheringham et al. 2002; Páez 2005). Multi-level approaches account for spatial heterogeneity by means of zone-specific random terms that are attached to individual-level coefficients. While this provides a powerful way to deal with variations in responses across the population, any variations that are detected remain unexplained (i.e. they are part of a random term). A second alternative, GWR is specifically excluded for our analysis for a number of reasons. First, geographical weights have been implemented for logistic, binary probit, and Poisson regression, but not for ordered probit. Second, estimation of GWR models is computationally expensive. Estimating linear models with more than a hundred thousand observations is not an easy task (Páez et al. 2008). Estimation times for non-linear models have not been reported but are likely to be substantially longer. Third, GWR tends to produce unwieldy sets of results, for which interpretation of the coefficients becomes complicated in models with a large number of independent variables. Finally, recent research offers cautionary evidence regarding the suitability of GWR coefficients for statistical inference (see Wheeler and Tiefelsdorf 2005; Páez and Wheeler 2009).

For this study, we elected to conduct geographical analysis based on the expansion method (Casetti 1972). This method models spatial variations by expanding the coefficients of an initial model (assumed to contain the knowledge of the process), as functions of expansion variables (in this case, spatial coordinates). The result is a model that incorporates spatial variations, and is called the terminal model. Unlike the multi-level approach, this method reflects variations over space as an expansion of deterministic coefficients. By doing so, any variation detected can be explicitly related to known variables (for example location). Use of deterministic expansions greatly facilitates the visualization and interpretation of results. The method is also more convenient for producing forecasts than multi-level models which, just as in the case of mixed logit models, require simulations to produce forecasts. The method is described next.

Consider the following utility function. The utility is specified using a combination of fixed coefficients ($\boldsymbol{\beta}$) associated with a vector of explanatory variables $\boldsymbol{X}_i$ and a set of expansion coefficients $\boldsymbol{\alpha}_i$ associated with a vector of explanatory variables $\boldsymbol{Z}_i$:

$$U_i = Z_i\alpha_i + X_i\beta + \varepsilon_i \tag{6}$$

The subscripts in the utility in Eq. 6 denote decision maker i at location i. Vector $\boldsymbol{\alpha}_i$ is of size m by 1 and includes a constant term. Each of m coefficients in this vector can be expanded in the following way to produce a trend surface of order 1:

$$\alpha_{im} = \alpha_{im,1} + \alpha_{im,2}u_i + \alpha_{im,3}v_i \tag{7}$$

Or a trend surface of order 2:

$$\alpha_{im} = \alpha_{im,1} + \alpha_{im,2}u_i^2 + \alpha_{im,3}u_i + \alpha_{im,4}u_iv_i + \alpha_{im,5}v_i + \alpha_{im,6}v_i^2 \tag{8}$$

The components of the location-specific coefficient are a region-wide (i.e. spatially constant) mean $\alpha_{im,1}$, and other coefficients associated with the coordinates u_i (easting) and v_i (northing) in a polynomial expansion. In this way, the model incorporates the typical fixed coefficients (constant throughout the population) and coefficients that incorporate spatial variability (that is, they are specific to each location). Since the trend surface is linked to a variable in vector $\boldsymbol{Z}_i$, it can be seen that the expansion essentially is the interaction between a variable and a location, and can therefore be used to represent a geographically explicit response surface for that variable (see Morency et al. 2010). In this application three variables are spatially expanded, namely the indicator variables for people aged 65+, single parents, and (in Montreal) low income families (<$20K). The expansion is based on the use of the coordinates, using a quadratic trend, and distance to the Central Business District of the corresponding urban area. All other model coefficients are fixed. Table 3 shows the model results for Hamilton, Toronto and Montreal.

Key observations about the spatial expansion are as follows: the overall goodness of fit of the model assessed by means of the ρ^2 and adjusted ρ^2 statistics shows that the model with spatial expansion improves slightly over the restricted model in all three models. A likelihood ratio test can be computed using the deviance. For example, in the case of Hamilton, the information gains of the spatial versus the non-spatial models are determined in the following way: $41984.605 - 41920.202 = 64.403$. This is the value of the likelihood ratio test, and can be compared against the χ^2 distribution with $27 - 19 = 8$ degrees of freedom (the difference in the number of explanatory variables in the restricted and unrestricted models). The likelihood ratio test is significant at the $p < 0.0000$ level for all three cases. Significance testing of the spatial effect is performed in the usual way by means of the p values, and as seen in Table 3, the spatial expansions have significant components for every variable expanded. Preliminary examination of the parameters of the surfaces reveals that space plays a role, and that this role is specific to the city and population segment under examination.

In terms of the results, we first note the impact of introducing spatially expanded coefficients on the coefficients in the non-expanded model. A majority of the fixed coefficients remain more or less the same between Tables 2 and 3 and the ordered probit thresholds λ_1, λ_2, and λ_3 do not change appreciably. The coefficients of the spatially expanded variables change, but the changes are due to the introduction of the spatial trend. To understand the operation of these coefficients, it is convenient to consider an example. This is shown in Table 4, using the case of the coefficient for age 65+ in Montreal. Whereas the fixed coefficient for this variable in Table 2 is -0.4906, in the spatial expansion the coefficient is a function of the coordinates, and can be evaluated at various locations to give a spatially varying coefficient. As seen in Table 4, the expanded coefficient is composed of the various individual coefficients for age 65+, and the quadratic expansion is interacted with the age 65+ variable. The spatially expanded coefficient is the sum of these coefficients, evaluated at specific locations, in the example the CBD (distance from CBD is zero, and the normalized coordinates are $u = 0.64$ and $v = 0.43$) and the most distant point from the CBD (with normalized coordinates $u = 1.00$ and $v = 0.98$, and normalized distance from the CBD 0.6573). The value of the coefficient at these locations is -0.2991 and -0.5171, respectively. The spatially expanded coefficient can be evaluated at any location, but the example shows that although the direct effect of age +65 changes signs between Tables 2 and 3, the net effect is still negative, if increasingly so from the CBD. Clearly, the fixed coefficient in Table 3 underestimates the effect of age at suburban locations, and overestimates it at central locations. Similar changes can be observed for other spatially expanded coefficients: the only income coefficient that changes is that for low income (<$20K), and the only household structure variable that changes is the indicator for single parent households (and this coefficient still only becomes significant in Montreal).

Table 3 Ordered probit models with spatially expanded coefficients

	Hamilton, 2001		Toronto, 2001		Montreal, 2003	
$L(\beta)$	−20960.101		−105614.4		−113969.179	
$L(c)$	−22931.483		−119332.053		−125299.787	
ρ^2	0.0860		0.1150		0.0904	
$\bar{\rho}^2$	0.0848		0.1147		0.0901	
Deviance (−2 * logL)	41920.202		211228.801		227938.358	
n	22837		126319		150608	
Variable	Estimate	p value	Estimate	p value	Estimate	p value
Constant	−0.1234	0.0540	−0.5142	0.0000	0.3571	0.0000
Thresholds (for identification: threshold 1 = 0)						
λ_2	2.0647	0.0000	2.2290	0.0000	2.4118	0.0000
λ_3	2.8880	0.0000	3.0485	0.0000	3.2857	0.0000
λ_4	3.4743	0.0000	3.6095	0.0000	3.8700	0.0000
Age						
<20	0.1835	0.0000	0.3524	0.0000	0.0745	0.0000
20–35	−0.1195	0.0000	−0.1088	0.0000	−0.0348	0.0001
36–50	Reference		Reference		Reference	
51–64	−0.0439	0.0438	−0.0742	0.0000	−0.0813	0.0000
65+	−3.7310	0.0000	−1.3743	0.0000	0.6459	0.0061
Income						
Income (CT average)	0.1065	0.0000	0.0242	0.0000	–	
Income^2 (CT average)	−0.0060	0.0000	−0.0003	0.0000	–	
Refuse/don't know	–		–		−0.4007	0.0000
<20K	–		–		–	
20–40K	–		–		−0.1875	0.0000
40–60K	–		–		−0.1328	0.0000
60–80K	–		–		−0.0827	0.0000
80–100K	–		–		−0.0526	0.0004
>100K	–		–		Reference	
Household structure						
Single	Reference		Reference		Reference	
Couple	−0.3286	0.0000	−0.2548	0.0000	−0.0884	0.0000
Couple W/children	−0.1382	0.0026	−0.1567	0.0000	–	
Single parent	–		–		–	
Other	−0.4457	0.0000	−0.4161	0.0000	−0.2142	0.0000
Mobility tools						
Driver license	0.4737	0.0000	0.5206	0.0000	0.3858	0.0000
Vehicle own	0.3259	0.0000	0.1964	0.0000	0.0970	0.0000
*Age 65+	0.3130	0.0000	0.3667	0.0000	0.3352	0.0000
*Low income	–		–		–0.0993	0.0000
*Single parent	0.3855	0.0000	0.1271	0.0001	–	

Table 3 continued

	Hamilton, 2001		Toronto, 2001		Montreal, 2003	
Variable	Estimate	p value	Estimate	p value	Estimate	p value
Transit within 500 m	–		−0.0686	0.0000	0.0588	0.0023
*Age 65+	−0.3989	0.0017	–		0.1217	0.0134
*Low income	–		–		–	
Occupation						
Full time employment	0.6582	0.0000	0.7848	0.0000	0.6458	0.0000
*Single parent	0.2374	0.0149	0.1297	0.0011	0.1363	0.0005
Part time employment	0.5193	0.0000	0.5060	0.0000	0.6135	0.0000
*Age 65+	–		0.2551	0.0000	0.1579	0.0128
*Single parent	−0.2625	0.0335	–		–	
Student	0.4420	0.0000	0.4984	0.0000	0.6524	0.0000
Free parking at work	–		0.0441	0.0000	0.3340	0.0000
Urban form						
Population density	−0.0306	0.0223	0.0071	0.0206	0.0092	0.0000
Spatial expansion						
Distance to CBD	−0.4819	0.0005	1.0012	0.0000	–	
*Age 65+	1.8007	0.0023	1.7181	0.0000	−1.0698	0.0000
*Low Income	–		–		−0.1764	0.0163
*Single Parent	−1.2951	0.0199	–		0.3679	0.0032
u^2	–		−1.1610	0.0000	–	
*Age 65+	−5.0424	0.0014	−2.1077	0.0000	1.5460	0.0007
*Low Income	–		–		0.7688	0.0000
u	–		1.2197	0.0000	–	
*Age 65+	5.7806	0.0023	2.4772	0.0000	−1.9826	0.0004
*Low Income	–		–		−0.7510	0.0000
*Single Parent	–		–		0.1431	0.0026
v	–		0.2468	0.0134	0.5687	0.0000
*Age 65+	8.4979	0.0000	–		−1.8132	0.0002
v^2	–		−1.0596	0.0000	−0.7377	0.0000
*Age 65+	−11.1925	0.0000	−1.6144	0.0000	1.9585	0.0001

An important consequence of estimating spatially expanded coefficients is that the trip making probability is not constant across space (like in the model with fixed coefficients), but rather varies as the spatially expanded coefficients are evaluated at various locations. This effect is clearly displayed in Fig. 1, where the estimated trip rate surfaces for the reference group and for the three vulnerable population groups for each of the three urban centers can be seen. The reference group consists of single people aged 36–50, with income >$100,000, not employed and not students, with no driver's license, no vehicle and no access to a transit station within 500 m. The surface for the reference group results from changing urban form and spatial expansion variables that vary over space. Surfaces are similarly computed for each vulnerable population group for which spatial expansion coefficients are modified.

Besides changes to coefficients directly affected by the introduction of the spatial expansion, the only other coefficients that change in a noticeable way are those related to

Table 4 Example of evaluation of a spatially expanded coefficient (age 65+ in Montreal) at two different locations

Variable	Coefficient	At CBD (u = 0.64, v=0.43)		At max dist (u = 1.00, v = 0.98)	
Age 65+	0.6459	1.0000	0.6459	1.0000	0.6459
Distance to CBD	–	–	–	–	–
*Age 65+	−1.0698	0.0000	0.0000	0.6573	−0.7032
u^2	–	–	–	–	–
*Age 65+	1.5460	0.4096	0.6332	1.0000	1.5460
u	–	–	–	–	–
*Age 65+	−1.9826	0.6400	−1.2688	1.0000	−1.9826
v	0.5687	0.4300	0.2445	0.9800	0.5573
*Age 65+	−1.8132	0.4300	−0.7797	0.9800	−1.7769
v^2	−0.7377	0.1849	−0.1364	0.9800	−0.7229
*Age 65+	1.9585	0.1849	0.3621	0.9800	1.9193
Spatially expanded coefficient			−0.2991		−0.5171

population density. Unlike the models reported in Table 2, population density is significant and positive *both* in Toronto and Montreal, and significant and negative in Hamilton. This result is sensible, given that Toronto and Montreal have vibrant central cities, whereas Hamilton's historical CBD is considerably more depressed.

With respect to the city-specific findings, we observe that in Hamilton the spatial variables for the reference group all have non-significant coefficients, except for the distance to CBD variable. The effect is relatively muted, leading to only small trip rate variations across space as seen in Fig. 1a, which implies that little spatial heterogeneity for the reference population can be found beyond that explained by the socioeconomic variables in the model. Still, it is important to note that the model in Table 2 does not accommodate even what little variation is detected in the trip generation rate, but rather assumes that the rate is "flat", or in other words, constant regardless of location. Given the magnitude of the effect for the reference group this may not be hugely misleading. It would be, however, in the case of seniors in the city of Hamilton, since it can be seen that the spatial expansion for this cohort has various significant components, which translate into a trip rate surface with a dramatically different aspect, as seen in Fig. 1b. For the elderly, mobility is higher in the city and drops off dramatically in the suburban areas. Also apparent is a "ridge" of elevated mobility for seniors along the u-axis, which coincides with higher quality transportation infrastructure and services along the major East-West corridor through the City of Hamilton. For single parent families, distance to the CBD is the only significant spatial component, but the effect is greater than for the reference group, also leading to a more dramatic decrease in trip making with distance from the CBD than the reference population.

In Toronto, examination of the spatial coefficients tells a different story. First, in contrast to the City of Hamilton, the spatially expanded variables for the reference group are all statistically significant. These spatial differences in mobility for non-vulnerable populations may simply be due to congestion effects on trip generation, which are more serious in Toronto than in Hamilton (this may also have to do with the larger sample size in Toronto, a much larger city). The trend surface is relatively flat, but does show higher trip generation rates in the east part of the city, and lower levels downtown and in the northwest. In Toronto, the spatial coefficients do change for the elderly (except for the u $\times$ v and the v coefficients), but do not change in any significant way for single parents.

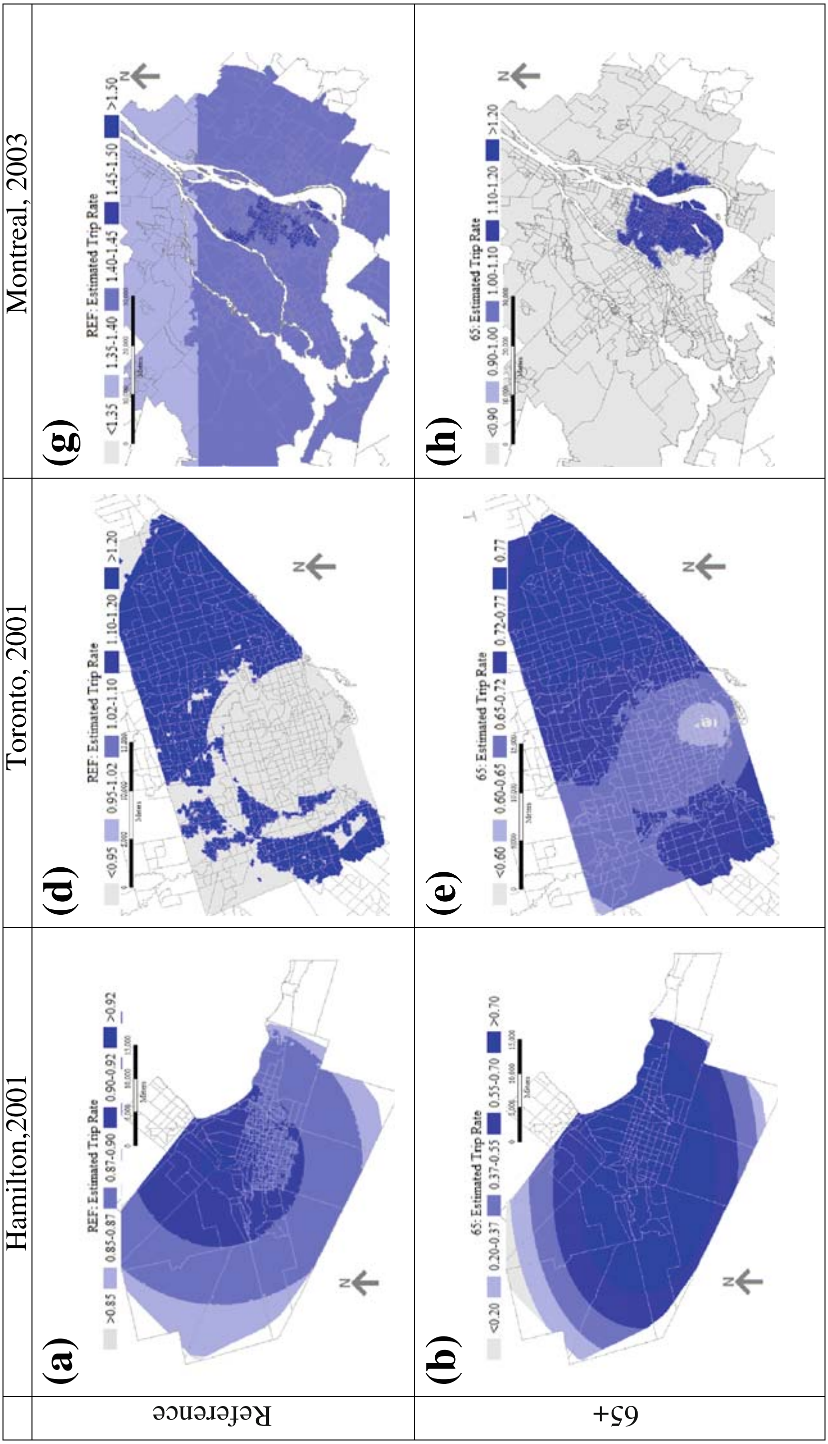

Fig. 1 Trip generation surfaces by population group (assuming no transit and no auto-ownership)

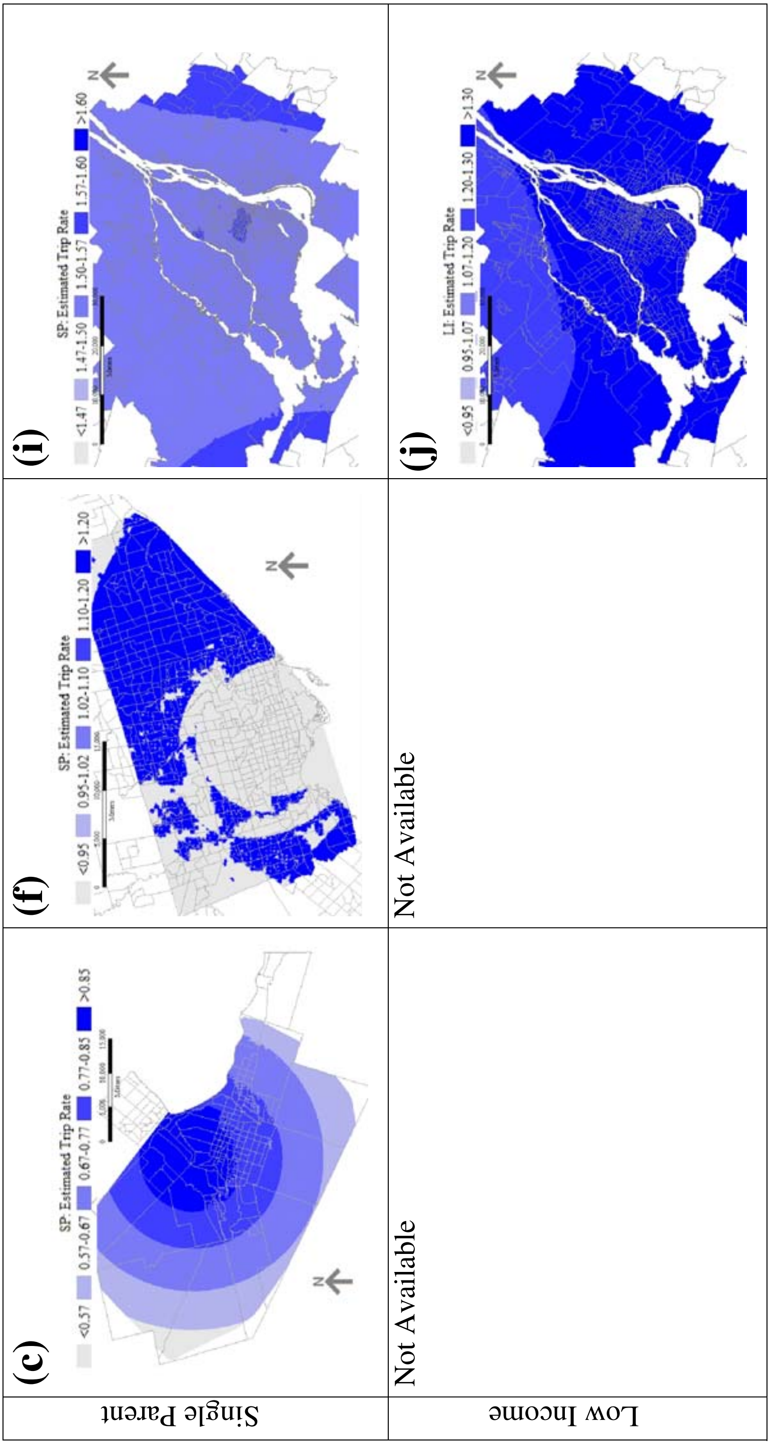

Fig. 1 continued

The differences in spatial mobility patterns for the elderly in Toronto show that the pattern is similar to that of the reference group, but with a more pronounced decrease in mobility from east to west.

In Montreal, the spatial coefficients are only statistically significant for the reference group in the north-south direction (v-axis). In the north-south direction, mobility for the reference group decreases with distance from the centre of Montreal, although the trip rate surface is relatively flat. As for Toronto, the most important deviations from the reference group in Montreal are for the elderly population. The mobility of the elderly population is high in the central core and decreases quickly with distance from the central core of Montreal. This can be explained by the high number of opportunities accessible in the central core, namely by foot, while opportunities are more dispersed in suburban areas as well as lower level of service for transit. Because Montreal collects information about income, it is possible to also show the mobility surface for the low-income cohort. This surface is rather complex, but appears to indicate lower levels of accessibility as one leaves the central area of Montreal to the north or south, and an increase in accessibility as one leaves to the east or west, ceteris paribus. In Montreal, the spatial parameters for single family households are very small, so the mobility surface is quite flat and similar to that of the reference group.

Clearly our second hypothesis, that there are systematic variations in mobility over space that cannot be captured solely by explanatory variables, is validated. There are statistically significant spatial expansion variables in all three cities for the reference population. This analysis has lent partial support to the third hypothesis, showing that there are spatial variations that are different for some of the vulnerable groups than for the general population, although the spatial variations are somewhat different from city to city. In both Hamilton and Montreal, the mobility rates for the elderly tend to reduce significantly with distance from the CBD, while Toronto shows the opposite trend. The mobility rates of single family parents do not appear to differ much from the rates of the reference population. Spatial expansion of low income households (conducted only for Montreal), shows somewhat complex results, but ultimately confirms a reduction in trip making as one moves outside the CBD.

Conclusions

As the transportation dimension of social exclusion research has garnered attention, it has been argued that the dominant categorical approach in research has tended to overlook important policy questions of a spatial nature, that relate to the allocation of limited resources (Church et al. 2000). In order to provide a spatial perspective onto the issue of mobility and social exclusion, in this paper we have examined the trip generation rates of three vulnerable populations (the elderly, low income individuals, and people in single parent households) vis-à-vis the reference population in three major Canadian metropolitan areas. The combination of an ordered probit approach with spatially expanded coefficients has proven to be a useful tool for analysis that allows us to better capture the inherent spatial nature of travel behavior. The approach allows not only for the identification of spatial variations in behavior, but also, by producing location-specific coefficients, for a convenient visualization of differences in mobility over space for different population groups, after other socio-economic characteristics have been taken into account.

Observations from the ordered probit model (without spatial expansion) lend support to the conclusions of previous trip generation studies found in the literature. Furthermore, they are generally consistent with the notion that some groups in society display more limited levels of mobility, although whether this is a matter of preference or otherwise, the models cannot tell. For instance, trip generation is lower for lower income individuals in Montreal, and for individuals in lower income census tracts in Hamilton and Toronto. There is evidence as well of lower trip making propensity for the elderly, although the effect of age is cancelled by auto ownership. Interestingly, only minor differences were found for individuals in single parent households. Other research, in contrast, indicates that individuals in this population segment tend to have significantly smaller activity spaces, as measured by mean distance traveled (Morency et al. 2010). Other factors that positively correlate with trip generation include, ownership of a driver license, employment, being a student, having free parking at work, and living in a single-person household. One measure of the physical environment, namely population density, showed mixed results for the different cities, as did proximity to transit.

In support of the first hypothesis, the analysis found the following key differences between the impact of employment and mobility tools on vulnerable populations and the impact on the general population:

- The trip generation of the elderly (65+) is more influenced by vehicle ownership than the rest of the population. The effects of transit proximity and employment are also generally greater for the elderly population, but these effects are less pronounced than for auto ownership.
- For single parents, vehicle ownership and full time employment have a more important effect than for the reference population, but not for transit access.
- Trip generation rates of low income individuals are less influenced by vehicle ownership and more influenced by transit proximity than are the rest of the population.

The second hypothesis is that there are systematic contextual variations in mobility over space that cannot be captured solely by explanatory variables, but that can be captured through spatial expansion of coefficients. This has been proven for Hamilton, Toronto and Montreal, although it should be pointed out that the effects are different for each of the urban areas.

The third hypothesis is that these systematic variations are different for vulnerable groups than for the general population. When spatial expansion is introduced separately for vulnerable groups, none of the above conclusions change, however, several additional conclusions are made thus lending support to the third hypothesis. Because they deal with space, these conclusions are different for each urban center.

- For Hamilton, mobility for both the elderly and for single parent families decreases in the suburban areas, away from key transit corridors.
- For Toronto, differences in mobility occur, especially for the elderly, from east to west, with the lowest levels of mobility occurring in the northwest of the city, a low income area. Single parent families do not exhibit any geographic differences from the rest of the population.
- For Montreal, the most important differences in mobility for the reference population occur along the north–south axis of the city, the mobility of the elderly decreases with distance from the central core, no geographic differences are found in the population of single parent families, and low income families experience greater mobility than the reference population to the east and west but lower mobility in the north and south of the downtown.

Although the focus of this research is on knowledge building, some elements analyzed in this paper provide insights for policy intervention. Regarding mobility tools, there is evidence that private vehicles have the largest impact on mobility, and may be essential to maintain current levels of mobility (and consequently accessibility), especially in suburban areas. While this fact supports the implementation of programs that promote auto ownership and use, and such programs exist in a number of countries (e.g. Fol et al. 2007; Wachs and Taylor 1998), automobility is associated with well-understood environmental and economic impacts related to resource consumption. There have also been warnings that reliance on private mobility may contribute to decline in social capital and may thus entail other hidden costs that are not yet fully understood (see Farber and Páez 2009). It is important to keep in mind the potential contradictions between environmental, economic, and social policy, vis-à-vis the promotion of private mobility. As an alternative, the evidence linking transit access to mobility is mixed, despite the considerable advantages of public transportation from an environmental and resource consumption perspective.

Other policies to increase mobility may involve the provision of employment or training opportunities for individuals, resulting in both higher levels of income and employment. The results of the study provide support for the promotion and formulation of policies and programs that consider the specific needs and requirements of vulnerable populations. Consideration of the special circumstances of vulnerable groups is important to ensure that any policy efforts are effective. Similarly, this study reported on the significant regional differences that exist in travel behavior of individuals living in each of the three urban areas that were analyzed. These results point to the need for geographic-based approaches in policy and planning.

The identified spatial variations in trip generation also provide important clues about which parts of the analyzed cities that vulnerable populations may experience greater degrees of social exclusion. They also provide an opportunity to help prioritize transportation infrastructure projects or other social programs to take into account the needs of vulnerable populations with the lowest levels of mobility.

Limitations of this research center on some shortcomings of the datasets that have been used for the analysis. Although the Toronto Area operates one of the largest household travel surveys in the world, the Toronto Area survey does not ask about household income, and does not collect information about non-motorized trips to non-work / non-school activities. Proxy reporting leads to some under-reporting of trips in the survey, a fact that leads to imperfect comparisons between cities. With regards to complementary research, as we pointed out initially, trip generation is but one indicator of mobility, and by no means a sufficient indicator of social exclusion. In particular, a more refined view of mobility and social exclusion can be attained by extending the analysis to consider distance traveled, a mobility indicator that provides a valuable measure of the extent of daily activity spaces. Distance traveled in the cities of Hamilton, Montreal, and Toronto, is analyzed in a paper by Morency et al. (2010). The question remains too of what are the accessibility implications of mobility outcomes given a surrounding opportunity landscape. Analysis of distance traveled also is useful in addressing this question in specific case studies that examine the accessibility by low income individuals to food services in Montreal (Páez et al. 2010) and accessibility to employment by single parent households in Toronto (Páez et al. Unpublished manuscript available from the authors). Along with the present research, these companion papers provide a more complete picture of transport-related social exclusion issues in Canadian urban areas.

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References

Abrahamson, P.: Researching poverty and social exclusion in Europe. J. Eur. Soc. Policy **13**(3), 281–285 (2003)

Badoe, D.A.: Forecasting travel demand with alternatively structured models of trip frequency. Transp. Plan. Technol. **30**(5), 455–475 (2007)

Badoe, D.A., Chen, C.: Modeling trip generation with data from single and two independent cross-sectional travel surveys. ASCE J. Urban Plan. Dev. **130**(4), 167–174 (2004)

Ben-Akiva, M., Lerman, S.: Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press, Cambridge (1985)

Benekohal, R.H., Michaels, R.M., Shim, E. Resende, P.T.V.: Effects of aging on older drivers' travel characteristics. In: Paper presented at the 73rd Annual Meeting of the Transportation Research Board, Washington, DC (1994)

Bhat, C.R., Zhao, H.: The spatial analysis of activity stop generation. Transp. Res. B **36**(6), 557–575 (2002)

Boarnet, M.G., Sarmiento, S.: Can land-use policy really affect travel behavior? A study of the link between non-work travel and land use characteristics. Urban Stud. **35**(7), 1155–1169 (1998)

Bourne, L.: Social change in Central Ontario, vol. 8. Neptis Foundation, Toronto (2003)

Bullard, R.: Sprawl City: Race, Politics, and Planning in Atlanta. Island Press, Washington, DC (2000)

Bush, S.: Forecasting 65+ travel: an integration of cohort analysis and travel demand modeling. PhD Thesis, MIT (2003)

Casetti, E.: Generating models by the expansion method: applications to geographic research. Geogr. Anal. **28**, 281–298 (1972)

Chu, X.: The effects of age on the driving habits of the elderly: evidence from 1990 national personal transportation studies. Research and Special programs Advisory Report No. DOT-T-95-12, USDOT (1994)

Church, A., Frost, M., Sullivan, K.: Transport and social exclusion in London. Transp. Policy **7**(3), 195–205 (2000)

Currie, G.: Quantifying spatial gaps in public transport supply based on social needs. J. Transp. Geogr. doi: 10.1016/j.jtrangeo.2008.12.002 (2009, in press)

Deka, D.: Transit availability and automobile ownership: some policy implications. J. Plan. Educ. Res. **21**, 285–300 (2002)

Farber, S., Páez, A.: My car, my friends, and me: a preliminary investigation of automobility and social activity participation. J. Transp. Geogr. **17**(3), 216–225 (2009)

Fol, S., Dupuy, G., Coutard, O.: Transport policy and the car divide in the UK, the US and France: beyond the environmental debate. Int. J. Urban Reg. Res. **31**(4), 802–818 (2007)

Fotheringham, S., Brundson, C.: Local forms of spatial analysis. Geogr. Anal. **31**(4), 340–358 (1999)

Fotheringham, S., Brundson, C., Charlton, M.: The analysis of spatially varying relationships. Wiley, Chichester (2002)

Georggi, N.L., Pendyala, R.M. (2001) An analysis of long distance travel behavior of the elderly and low income. Personal travel: the long and short of it. In: Conference Proceedings, Transportation Research E-Circular Number E-C026, Transportation Research Board, National Research Council, Washington, DC, pp. 121–150

Giuliano, G.: Low income public transit and mobility. Transp. Res. Rec.: J. Transp. Res. Board **1927**, 63–72 (2005)

Greene, W.H.: Econometric Analysis, 5th edn. Prentice Hall, Upper Saddle River (2002)

Habib, K.M.N., Carrasco, J.A., Miller, E.J.: The social context of activity scheduling: a discrete-continuous model of the relationship between 'with whom' and episode start time and duration. Transp. Res. Rec. **2076**, 81–87 (2008)

Institute of Transportation Engineers: Trip generation manual, 7th edn. ITE, Washington, DC (2004)

Kenyon, S.: Understanding social exclusion and social inclusion. Proc. Inst. Civil Eng. Munic. Eng. **156**(2), 97–104 (2003)
Kenyon, S., Rafferty, J., Lyons, G.: Social exclusion and transport in the UK: A role for virtual accessibility in the alleviation of mobility-related social exclusion? J. Soc. Policy **32**, 317–338 (2003)
Limtanakool, N., Dijst, M., Schwanen, T.: On the participation in medium- and long-distance travel: a decomposition analysis for the UK and the Netherlands. Tijdschr. Econ. Soc. Geogr. **97**(4), 389–404 (2006)
Litman, T.: Evaluating Transportation Equity: Guidance for Incorporating Distributional Impacts in Transportation Planning. Victoria Policy Institute, Victoria (2007)
Lucas, K.: Running on Empty: Transport: Social Exclusion and Environmental Justice. Policy Press, Bristol (2004)
Lyons, G.: The introduction of social exclusion into the field of travel behaviour. Transp. Policy **10**(4), 339–342 (2003)
McCray, T., Brais, N.: Exploring the role of transportation in fostering social exclusion: the use of GIS to support qualitative data. Netw. Sp. Econ. **7**(4), 397–412 (2007)
McDougall, L.: Aging baby boomers and what it means for domestic travel in the 21st century. Travel-Log Stat. Can. **17**(3), 1–8 (1998)
Mercado, R.G., Páez, A.: Determinants of distance traveled with a focus on the elderly: a multilevel analysis in the Hamilton CMA, Canada. J. Transp. Geogr. **17**(1), 65–76 (2009)
Miller, H.J.: Potential contributions of spatial analysis to geographic information systems for transportation (GIS-T). Geogr. Anal. **31**(4), 373–399 (1999)
Miller, H.J.: Social exclusion in space and time. In: Axhausen, K.W. (ed.) Moving Through Nets: The Social and Physical Aspects of Travel, pp. 353–380. Elsevier, Oxford (2006)
Mokhtarian, P.L.: If telecommunication is such a good substitute for travel, why does congestion continue to get worse? Transp. Lett. **1**(1), 1–17 (2009)
Morency, C., Páez, A., Roorda, M.J., Mercado, R.G., Farber, S.: Distance traveled in three Canadian cities: spatial analysis from the perspective of vulnerable population segments. J. Transp. Geogr. doi: 10.1016/j.jtrangeo.2009.09.013 (2010, in press)
Newbold, K.B., Scott, D.M., Spinney, J.E.L., Kanaroglou, P., Páez, A.: Travel behavior within Canada's older population: a cohort analysis. J. Transp. Geogr. **13**(4), 340–351 (2005)
Ortúzar, J.D., Willumsen, L.G.: Modelling Transport, 3rd edn. Wiley, Chichester (2001)
Páez, A.: Exploring contextual variations in land use and transport analysis using a probit model with geographical weights. J. Transp. Geogr. **14**(3), 167–176 (2005)
Páez, A.: Spatial perspectives on urban systems: developments and directions. J. Geograph. Syst. **9**(1), 1–6 (2007)
Páez, A., Long, F., Farber, S.: Moving window approaches for hedonic price estimation: an empirical comparison of modelling techniques. Urban Stud. **45**(8), 1565–1581 (2008)
Páez, A., Mercado, R.G., Farber, S., Morency, C., Roorda, M.: Relative accessibility indicators for urban settings: definitions and application to food deserts in Montreal. Urban Stud. doi:10.1177/0042098009353626 (2010, in press)
Páez, A., Scott, D.M.: Spatial statistics for urban analysis: a review of techniques with examples. GeoJournal **61**(1), 53–67 (2004)
Páez, A., Scott, D.M., Potoglou, D., Kanaroglou, P.S., Newbold, K.B.: Elderly mobility: demographic and spatial analysis of trip making in the Hamilton CMA. Urban Stud. **44**(1), 123–146 (2007)
Páez, A., Wheeler, D.: Geographically weighted regression. In: Kitchin, R., Thrift, N. (eds.) The International Encyclopedia of Human Geography. Elsevier, Oxford (2009)
Poon, L.W., Jang, Y., Reynolds, S.G., McCarthy, E.: Profiles of the oldest-old. In: Johnson, M.L. (ed.) The Cambridge Handbook of Age And Ageing, pp. 346–353. Cambridge University Press, Cambridge (2005)
Roorda, M.J., Morency, C., Woo, K.: Two cities, two realities? A closer look at the evolution of trip rates in Toronto and Montreal. TRR: J. Transp. Res. Board **2082**, 156–167 (2008)
Rosenbloom, S: Travel by the elderly. In: 1990 Nationwide Personal Transportation Survey. Demographic Special Reports, Chapter III. USDOT. (1990)
Schmocker, J.D., Quddus, M.A., Noland, R.B., Bell, M.G.H.: Estimating trip generation of elderly and disabled people—analysis of London data. Management and Public Policy ISSN: 0361-1981, pp. 9–18 (2005)
Scott, D.M., Kanaroglou, P.S.: An activity-episode generation model that captures interactions between household heads: development and empirical analysis. Transp. Res. B **36**(10), 875–896 (2002)
Scott, D.M., Horner, M.W.: Examining the role of urban form in shaping people's accessibility to opportunities: an exploratory spatial data analysis. J. Transp. Land Use **1**(2), 89–119 (2008)

Scott, D.M., Newbold, K.B., Spinney, J.E.L., Mercado, R.G., Páez, A., Kanaroglou, P.S.: New insights into senior travel behavior: The Canadian experience. Growth Change **40**(1), 140–168 (2009)
Smith, G.C., Sylvestre, G.M.: Determinants of the travel behavior of the suburban elderly. Growth Change **32**(3), 395–412 (2001)
Social Exclusion Unit: Making the connections: final report on transportation and social exclusion. HMSO, London (2003)
Solomon, J.: Transport and social exclusion. In: Proceedings of Seminar C of European Transport Conference, Homerton College, Cambridge, 11–13 September, Association for European Transport, Planning and Transport Research and Computation Education and Research, pp. 141–153 (2000)
Statistics Canada: Census of Population. Government of Canada. (2001, 2006)
Stradling, S., Carreno, M., Ferguson, N., Rye, T., Halden, D., Davidson, P., Anable, J., Hope, S., Alder, B., Ryley, T., Wigan, M.: Scottish household survey topic report: accessibility and transport. Government of Scotland. (2005)
Todman, L.C.: Reflections on social exclusion: What is it? How is it different from U.S conceptualizations of disadvantage? And, why Americans might consider integrating it into U.S. social policy discourse? In: Paper presented at the City Futures Conference, Chicago, 10–8 July (2004)
Train, K.: Discrete choice methods with simulation. Cambridge University Press, Cambridge (2003)
Vance, C., Iovanna, R.: Gender and the automobile: an analysis of non-work service trips. In: Paper presented at the 86th Annual Meeting of the Transportation Research Board, Washington, DC (2007)
Wachs, M., Taylor, B.D.: Can transportation strategies help meet the welfare challenge? J. Am. Plan. Assoc. **64**(1), 15–19 (1998)
Wheeler, D., Tiefelsdorf, M.: Multicollinearity and correlation among local regression coefficients in geographically weighted regression. J. Geograph. Syst. **7**(2), 187–191 (2005)
Zavoina, R., McElvey, W.: A statistical model for the analysis of ordinal level dependent variables. J. Math. Sociol. Summer, 103–120 (1975)

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