Travel behavior – built environment nexus: an investigation in the context of Halifax Regional Municipality

TRAVEL BEHAVIOR – BUILT ENVIRONMENT NEXUS: AN INVESTIGATION IN THE CONTEXT OF HALIFAX REGIONAL MUNICIPALITY

By

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PREFACE

This thesis is comprised of two papers:

Paper 1: An analysis of built environment and auto travel in Halifax Regional Municipality, Canada

Paper 2: Is trip chaining a desirable travel behavior? An investigation from the built environment perspective

The papers will be submitted to two journals – *Transportation Research Part A* and *Transportation* respectively. Both papers are co-authored by the supervisor. The author of the thesis was responsible for selecting the research topic, review of the literature, creating model variables, analysis of data, statistical modeling, interpretation of the results and writing the papers. The supervisor's contribution include providing most of the data used in both papers, help setting research questions, guiding the methodology, suggestion on interpretation and review of the papers.

ABSTRACT

Land use planning has gained popularity as a travel demand management strategy for the last two decades. Many urban authorities in North America have adopted smart growth policies in order to curb auto use and promote sustainable forms of travel, namely, public transit, bicycle and walking. The purpose of this study is to examine whether someone's travel behavior is influenced by the characteristics of the built environment where one lives and works. The study area is Halifax Regional Municipality, Nova Scotia, Canada. Two aspects of travel are analyzed for a weekday: total distance travelled by auto and average tour complexity. Separate models are developed for worker and non-worker by applying ordinary least square and spatial lag modeling techniques. The built environment variables are measured near home and workplace and at different geographical scales. The average auto distance and tour complexity are separately regressed against the built environment variables while personal characteristics, household attributes, preferences for residential location and transport mode, and meteorological conditions of survey days are accounted for. The results of auto distance models suggest that people living and working in high accessibility areas with mixed land uses make shorter travel by auto, which supports the claims of smart growth proponents. The built environment variables make significant contribution to the fitness of auto distance models. In case of tour complexity models, built environment variables also appear to be significant but with lower contribution to model R^2. The results suggest that non-workers, who live in poor accessibility areas, make more complex tours. Workers living in poorly accessible neighborhoods and working in highly accessible areas make complex commuting and work-based, non-work tours. It means that, workers compensate poor neighborhood accessibility by trip chaining near workplace. The findings would be helpful to evaluate the existing growth strategies in Halifax Regional Municipality. It also makes several contributions to the literature.

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1.1 Sprawl versus Smart Growth

The term “sprawl” is widely used in built environment literature. But, there is no concrete definition of sprawl as Dowling (2000) rightly puts “Sprawl unquestionably has an I-know-it-when-I-see-it quality to it” (p. 874). However, researcher agree on some characteristics that sprawl might display: (1) leapfrog or scattered development, (2) commercial strip development, or (3) large extent of low-density, single-use development (Ewing, 1997; Tsai, 2005). Smart growth is the development pattern which is the opposite of sprawl. According to the Smart Growth Network (SGN), smart growth is a compact, mixed-use, walking, bicycle and transit-friendly development (SGN, 1998). Such development aspects are also embodied within the concepts of “neo-traditional neighborhood”, “new urbanism” and “transit oriented development” (Crane, 2000; Kockelman, 1997).

Conceptually, the need for long-distance travel is reduced in a compact and mixed-use neighborhood since the opportunities are close by. Due to higher density, public transport is financially viable in such areas. Also, parking facilities would not be abundant in a compact neighborhood which is a natural restriction to auto use. Thus, theoretically, smart growth should promote transit and bar auto use (Cervero and Kockelman, 1997).

Over the last two decades smart growth and similar concept of development has gained popularity in the US and Europe as a tool to curb auto travel. There are several examples in the context of US – Washington State Growth Management Act, Central Puget Sound Vision 2020 (Frank and Pivo, 1994), Smart Growth legislation in Arizona and Tennessee in 1998 (Weitz, 1999), etc. In Europe, compact, mixed-use and transit oriented development have been adopted in Netherlands since 1980s (Schwanen et al., 2004).

1.2 Growth policy of Halifax Regional Municipality

The population of Halifax Regional Municipality (HRM) is estimated to increase from 359,000 in 2001 to anywhere between 411,000 and 484,000 in 2026, depending on the job growth. With better employment growth in the region, the population may increase by 125,000 (HRM, 2006).

Halifax Regional Municipal Planning Strategy (Regional Plan) is the current growth plan that HRM approved in 2006. It is a 25-year plan that encompasses strategies for land use and transportation in the region, amongst other sectors. The plan foresees a quarter of the future population growth in downtown area, half of the total growth in the existing suburbs and the rest quarter will be distributed throughout rural areas. The density of the existing urban core and suburban areas will be increased in 25 year period through infill development in order to make public transit financially viable. Along with the increase of density, the Regional Plan puts forward strategies for mixed use development. The HRM will invest in infrastructure and provide other incentives to encourage such development within the existing urban and suburban areas. In general, the urban area of the region will comprise several compact, mixed-use centers, connected by public transit (HRM, 2006).

The Regional Plan dedicates over $150 million on transportation projects, roughly half of which will be spent to improve public transit. There are several projects to construct new roadways and to increase the lanes of existing roadways (HRM, 2006). Currently, there is no transportation masters plan for the region. The Regional Plan has directives that HRM will prepare such a plan where emphasis will be given to improve existing public transit, pedestrian and bicycle facilities and to develop new bus rapid transit system.

1.3 The current study: built environment – travel behaviour link

It appears that urban authorities in North America, including Halifax Regional Municipality, are adopting smart growth policies to discourage auto use and promote public transit, walking and bicycling. The surge of research on this field since late 1980s also implies the popularity of this concept. There have been more than two hundred published studies so far (Ewing and Cervero, 2010). However, the findings on built environment[1] – travel behavior relation are still inconclusive (Joh et al., 2008; Shiftan, 2008). While some empirical studies find significant impact of built environment on travel

[1] In this study the "built environment" is defined as the physical features of an urban area which was built (e.g. building, road, etc.) or intervened (e.g. municipal park) by human.

behavior (Cao et al., 2010), others observe very little or no relation between the two (Pinjari et al., 2009).

The reason which makes it difficult to get a definitive grasp on this relation is: both travel behavior and built environment are multidimensional in nature (Bhat and Guo, 2007) and there are myriad of metrics through which they can be represented. Because of this, different studies conceptualize the TB-BE relation through different modeling techniques (Handy, 1996). The current study addresses these issues and seeks the answer to the question: “Does built environment influence travel behavior?” Specifically, the study tests the following hypotheses-

Hypothesis 1: People living and working in compact, mixed-use areas, where the opportunities are located close by, make shorter non-work trips by car than those living and working away from the opportunities.

Hypothesis 2: People living and working in low-density, single-use areas, away from the opportunities, link their trips by trip chaining in order to compensate the poor accessibility.

If the first hypothesis is found to be true, that is, built environment impacts auto travel distance even after socio-demographics and preferences for residential and travel modes are accounted for, the smart growth proposition will be validated for Halifax Regional Municipality. The second hypothesis stresses that people minimize the influence of built environment on their travel behavior by trip chaining. If the current study finds such evidence, the smart growth development might not influence people's travel behavior to the extent the policy makers are now hoping for.

The remainder of the study is organized as follows:

Chapter 2 examines the impact of built environment on auto travel distance while socio-demographics, attitude and other factors are accounted for. Chapter 3 looks at trip chaining behavior and how it is influenced by built environment personal as household and attitudinal characteristics are controlled for. Both chapters follow the same structure. Each sets out with an introduction where the research question or objective of the chapter is stated. Next, the research question is placed with a context of pertinent literature. The following section explains the data sources, variables and statistical techniques used. Then the results are discussed, followed by a conclusion and future research direction. Finally, Chapter 4 summarizes the study, briefly compares the major findings of Chapter 2 and 3, and points out the contribution of the study in literature and in growth management policy.

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2 An analysis of built environment and auto travel in Halifax Regional Municipality, Canada

2.1 Introduction

The last few decades have seen the exercise of various travel demand management instruments, such as, road pricing, congestion charging, car pooling, parking control, taxation on car and fuel, subsidization of public transport, urban design measures, and recent improvements in intelligent transport systems (Gärling and Schuitema, 2007). Amongst these, the urban design measures have gained popularity in the last two decades (Ewing and Cervero, 2010). The proponents of urban design measures argue that a low-density, single-use, dispersed settlement pattern (commonly termed as "sprawl") causes long-distance travel and auto dependency. They suggest that a compact, mixed-use development can curb long-distance-auto-oriented travel (Banister, 1999). A number of empirical studies have been conducted to examine this claim, but with contrasting outcomes. After over two decades of research on the travel behavior (TB) – built environment (BE) relation, the results are still inconclusive (Badoe and Miller, 2000; Joh et al., 2008; Shiftan, 2008). Findings from different studies vary substantially, from little or no significance (Schimek, 1996; Boarnet and Sarmiento, 1998; Crane and Crepeau, 1998; Krizek and Waddell, 2002; Pinjari et al, 2009) to moderate significance (Cervero and

Kockelman, 1997; Kitamura et al., 1997; Bagley and Mokhtarian, 2002) to a strong causal association between TB and BE (Frank et al., 2007; Cao et al., 2009b; Cao et al., 2010).

The reasons behind the uncertainty of the TB-BE link are: different ways of measuring TB and BE (elaborated in the following section); use of different geographical scales of measurement; diverse methods; and a variety of ways of controlling for the residential self-selection effect. The current paper addresses three of these issues. First, TB metric used in this paper for modeling is the auto distance travelled by a person in a weekday. This metric is chosen instead of other TB measures, such as, number of trips, mode choice, etc., because of its aptness in terms of policy. The auto distance was measured for a subset of overall travel, because some trips (such as, work, transportation assistance, and travel for in-home socialization) are less likely to be influenced by BE. Also, we only model the weekday travel because weekdays are more constrained by time (e.g. work hour) and there is more congestion on road during the weekdays than on weekends. For these reasons, BE is likely to have more influence on travel during the weekdays.

Second, we use a comprehensive set of BE variables comprising various 3Ds (density, diversity and design) as well as different accessibility measures (gravity, proximity and cumulative opportunity). They are measured near home and workplace. Third, different geographical scales are used to compute the BE variables. Fourth, spatial lag models are applied, in addition to linear regression, in order to control for spatial autocorrelation which verifies the consistency of the model parameters. Fifth, residential self-selection is accounted for by directly introducing attitudinal variables in the models. Overall, we sample the trips and days of the week which are more likely to be influenced by BE; we measure BE thoroughly, and model the TB and BE within a modeling framework that should produce consistent and efficient estimates of BE parameters. If we find none or very little impact of BE on TB in this setting, we can conclude with some certainty that the TB-BE relation is non-existent in our study area, at least based on cross-sectional data.

The next section briefly describes different issues on TB-BE relation, drawing from the literature. The subsequent section describes the data sources, variables and models used in the study. The next section discusses the model results followed by a conclusion and direction for future studies.

2.2 Background

Since 1990s, there have been over two hundred studies on the TB-BE relation (Ewing and Cervero, 2010). However, in general, the nature of this link remains inconclusive (Shiftan, 2008). In this section, we attempt to understand why there is a general lack of consensus on this matter by disentangling some issues concerning this line of research.

2.2.1 Representation of TB and BE

Both travel behavior and built environment are multidimensional in nature (Bhat and Guo, 2007) and different studies use different measures of TB and BE in statistical modeling (Handy, 1996). Travel behavior, for instance, is measured in a number of ways – as number and proportion of trips by different travel modes (e.g., Kitamura et al., 1997), overall trip distance (e.g., Handy et al., 2005), trip distance by different modes (e.g., Bagley and Mokhtarian, 2002), auto ownership (e.g., Chen et al., 2008), amongst other metrics. Recently, Fan and Khattak (2008) model the size of activity space which is the polygon connecting the major locations of an individual's out-of-home activities. Some studies include trips with all purposes (Lin and Yang, 2009); others focus on particular trips, shopping, for instance (Handy, 1996). But, the common practice is to model all non-work trips (Ewing and Cervero, 2010) because work trip-decisions depend largely on factors other than BE, such as, labor market, housing choice, and real estate market (Crane and Crepeau, 1998). The temporal resolution of most studies is one day (Chen et al. 2008) while some studies use the travel data of two (Boarnet and Sarmiento, 1998) or more days (e.g. Kitamura et al., 1997 use the total number of trips in three days).

BE measures can be broadly categorized as the 3Ds: density, diversity, and design (Cervero and Kockelman, 1997), and different types of accessibility measures, such as, gravity accessibility, proximity (shortest distance to an opportunity), and cumulative opportunity (number of opportunities within the neighborhood) (Scott and Horner, 2008). Handy (1993) use two types of gravity accessibility – local and regional; local accessibility being measured by including only the neighborhood opportunities. Also, some researchers (e.g. Schimek, 1996; Milakis et al., 2008) use the location of respondent's neighborhood in a regional context as proxy of regional accessibility. Generally, the BE metrics are objectively measured employing geographic information systems (GIS); but sometimes they are subjectively measured as respondents' perceptions (Handy et al., 2005).

2.2.2 Scale of TB and BE

Studies have presented travel metrics at three different levels – individual (e.g., Kockelman, 1997), household (e.g., Schimek, 1996), and aggregated to zones (e.g., Milakis et al., 2008). Amongst the three, the individual is the best unit of analysis, since individuals decides on travel based on their personal characteristics as well as household attributes.

In most of the earlier studies, the geographical scales of the BE were either census tract, traffic analysis zone (TAZ) or any other aggregate level (Handy, 1996). Although travel and BE data are easily available at these levels, the explanatory power of BE variables in a model is reduced because there is less variation of BE data than that of socio-demographic information (Cervero and Kockelman, 1997). This is why (and also because of data availability) most recent studies attempt to compute BE variables for each person, usually through a buffer around home. The size of the buffer is defined based on what could be the acceptable walking distance, generally ¼ mile (Boarnet and Sarmiento, 1998; Krizek and Waddell, 2002). Further, many researcher have argued against using a single scale of measuring the BE (Handy, 1996; Boarnet and Sarmiento, 1998; Guo and Bhat, 2007). Their argument is that different people perceive the built environment differently and the perceived size of the *neighborhood* varies across individuals depending on their cognitive maps (Schönfelder and Axhausen, 2003). Guo and Bhat (2007) explain conceptually and empirically how different scales of measurement of BE variables can better explain the TB-BE relation. They use 3 scales – 0.4 km, 1.6 km and 3.2 km and employ a multi-scale logit model of residential location choice. They observe certain variables are significant at a certain scale. For example, land-use mix is significant at 3.2 km while density is significant at 0.4 km.

2.2.3 Method

In addition to representing TB and BE in a multitude of ways, different techniques of conceptualizing the TB-BE relation have produced different sets of results. The methodologies employed so far include descriptive methods, different types of regressions, discrete choice models, and complex models (structural equation models, joint discrete choice models, etc.), among other techniques. An example of descriptive analysis is Handy (1996). She compares four neighborhoods (two traditional and two modern) in the San Francisco Bay area in terms of shopping trips and accessibility to shopping. She does not model the relation between TB and BE variables; rather she applies ANOVA tests and finds significant relations between these two while socio-demographic characteristics are controlled for.

The most widely used method in this line of research is multiple linear regression (Ewing and Cervero, 2010) where the dependent variable is a continuous measure of TB, such as number of trips, travel distance, etc. Initially, a base model is specified with the statistically significant personal and household characteristics. Next, BE variables are added to the base model and the improvement (if any) of model R^2 is observed (Cervero and Kockelman, 1997).

If the TB is measured in terms of discrete alternatives (for instance, mode choice),a utility maximization approach is applied. Crane and Crepeau (1998) applied such a method for the first time in the TB-BE literature. Here, a rational individual is assumed to optimize their utility from travel choice. How much utility an individual will derive from their travel decision depends on their characteristics, the BE variables, and other factors (Crane and Crepeau, 1998; Vance and Hedel, 2007).

When modeling multiple TB variables, recent works apply a system of interrelated equations, rather than multiple unrelated equations. This method is more robust due to the fact that one travel decision (e.g. auto use) is likely to impact others (e.g. trip chaining). If the dependent variables are interval or ratio, typically structural equation modeling (SEM) is applied. If nominal or ordinal TB variables are modeled, joint discrete choice modeling techniques are applied. For example, Lin and Yang (2009) adopt SEM to model number of trips by different modes in Taiwan, and find that the influence of density and land-use diversity on trip generation is mostly indirect which would be overlooked if linear regression was applied.

Handy et al. (2005) provide an excellent example of the fact that different methods can produce different outcomes of the TB-BE relation. Their first model, which is based on cross-sectional data, suggests that there is no statistically significant relation between these two. But, a second model, based on quasi-longitudinal data (respondents reported change of TB and BE) finds a significant, causal relation between TB and BE.

2.2.4 Residential self-selection

If people live in a walking-friendly neighborhood because they prefer to have groceries nearby and do not like to spend hours driving, the characteristics of their neighborhood does not have anything to do with their travel. Their preference for residential location and travel mode dictates the travel behavior. If the model does not account for such preferences, the apparently strong relation between TB and BE would be circumstantial, not causal. The BE variables in such models would be correlated with the error term and the BE parameters would be biased. Mokhtarian and Cao (2008) identify seven categories of techniques to account for residential self-selection. They are: direct questioning; selecting samples from particular residential locations, such as, urban core, suburb, etc.; inclusion of attitudinal variables in statistical models (e.g., Kitamura et al., 1997; inclusion of attitude variables in structural equations models; use of instrumental variables (IV) (e.g., Boarnet and Sarmiento, 1998); modeling the change of TB and BE (e.g., Handy et al., 2005), and jointly modeling the discrete choice of residential location and TB (e.g., Bhat and Guo 2007). In the IV technique, the BE variables are first modeled against some variables, called IVs, which are correlated with BE, but not with TB (thus

IVs are unrelated with the error term of the TB model). The predicted values of BE from the IV model are then placed in the TB model. The strengths and limitations of different methods are discussed by Mokhtarian and Cao (2008).

More recently, Cao et al. (2010) apply a new approach to account for residential self-selection, propensity score matching. They define respondents' residential location in four categories based on the distance from the city center. Thus, there are four pairs of locations. For each pair, they select two sets of paired individuals whose socio-economic and attitudinal characteristics are similar. Thus, the difference in vehicle miles driven (VMD) by the persons within each pair is the *true* effect of residential location or BE. They find that after controlling for self-selection, people living farther from the city center drive more. Also, they observe that the effect of residential location (that is, BE) on VMD is more than that of self-selection.

2.3 Methodology

2.3.1 Data sources

The area selected for this study is the Halifax Regional Municipality, Nova Scotia (Figure 2.1). The travel data used in this study came from Halifax Space-Time Activity Research (STAR) Project, which was conducted between April 2007 and May 2008. The travel data are extracted from the time-use dataset, which contains 2-days (48 hours) of activities of 1,971 randomly selected respondents. The respondents were randomly selected from the members over 15 years old of 1,971 households. The database contains the *what* (activity-type), *when*, *where*, and *with whom* information, among other attributes of each activity. The location of each activity was recorded through a Global Positioning System (GPS) device that each respondent carried throughout the survey period. The STAR dataset "represents the world's largest deployment of global positioning systems (GPS) technology for a household activity survey to date" (Spinney and Millward, 2010 p. 134).

The built environment variables are computed from the STAR land use (parcel level) dataset; a 2008 DMTI network data set; a 2006 building footprint and sidewalk data set obtained from the HRM department of Planning and Development Services, and 2006 Census of Canada. The socio-economic and attitudinal information were obtained from the STAR personal and household information datasets. Also, a set of meteorological variables are used in this study that were collected from Environment Canada's website for the weather station located in Halifax Stanfield International Airport[2].

[2] http://www.climate.weatheroffice.gc.ca/climateData/hourlydata_e.html?Prov=NS&StationID=6358&Year=2007&Month=4&Day=1&timeframe=1

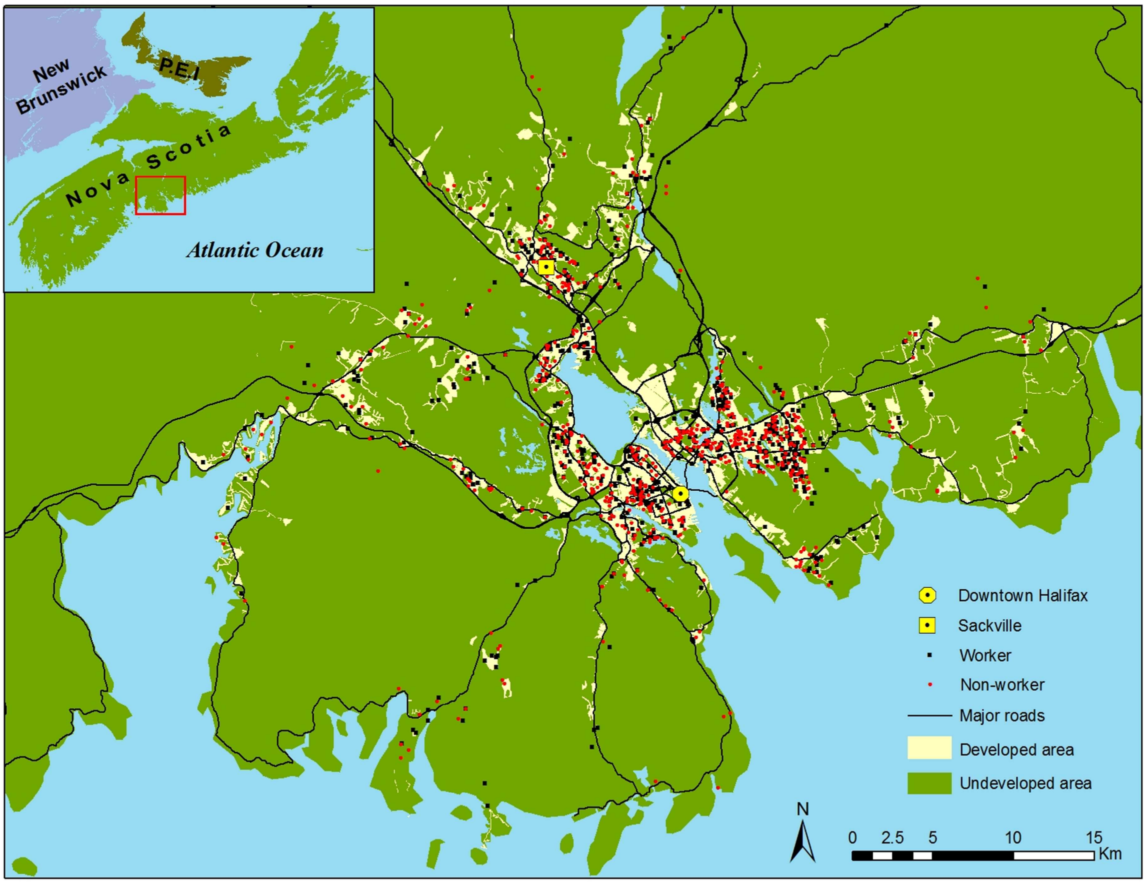

Figure 2.1: A part of the Halifax Regional Municipality displaying all respondents' (worker and non-worker) home locations

2.3.2 Variables

2.3.2.1 Travel variables

As discussed in the previous section, studies to date have used numerous measures of TB. For this study, we use daily distance travelled by personal vehicle, that is, personal-vehicle kilometers travelled (PKT) on weekdays. We selected the trips taken as both driver and passenger. The distance of a trip was computed by ArcGIS 9.3 as the shortest distance through the road network from the trip origin (latitude-longitude) to the destination[3]. We preferred this metric of TB over any other (number of trips by auto or any other mode) because the main focus of Smart Growth development is to reduce auto travel (Cervero and Kockelman, 1997); and intuitively distance is a better representation of road-usage and auto-emissions than trip frequency. For instance, the TB of a person who takes 10 short trips with a total distance of 15 kilometers is more preferable than someone who takes 5 trips covering a distance of 20 kilometers. The second person uses more road space and emits more harmful pollutants, such as, carbon monoxide and nitrogen oxides.

We excluded the weekend travel because it has been found that weekend travel behavior differs from that of weekdays due to fewer time constraints and better traffic conditions (Lee et al., 2009).We did not want to blend two types of behavior in the same

[3] For a multimodal trip (e.g., home – walk – bus – walk – grocery), the STAR dataset contains the GPS locations of only origin (home) and destination (grocery). We computed the distance of each trip-segment based on the duration of that trip segment and the average speed of transport mode. A median speed of auto (34 KPH) was used in the computation.

model. As mentioned in the introduction, in this study, our approach is to create the most suitable empirical context where we expect the TB-BE relation to be stronger than any other context. Since people have more time constraints and roads are more congested during the weekdays, we expect the TB-BE relation to be stronger on weekdays than it is on weekends.

The STAR time-use dataset provides two-day travel information, but we chose only one day because some of the survey-days were weekends. If a respondent's survey days were both on weekdays, we selected the day with most trips in order to have larger travel sample. This was applied to all respondents with two weekdays, thus the sample is not likely to be biased towards more trip-makers. We modeled separately the travel behavior of workers and non-workers. Further, we included only non-work trips since work travel-behavior is influenced more by non-BE factors, such as the housing market, labor market, etc. (Crane and Crepeau, 1998)[4]. Also, we excluded two types of non-work trips – transportation assistance (pick-up or drop-off) and travel for in-home socialization. The latter category was not included because these trips depend on one's social network, not the BE (Carrasco and Miller, 2006). The STAR dataset provides information on the trip-purpose of the primary respondent, not the trip purpose of other household members. Thus, it was not known whether the household member, who was picked up or dropped off, was

[4] Both work and school are referred to as "work".

going to work or to friend's place to socialize. The non-work trips that we chose are trips to any *opportunity*, like grocery, restaurant, religious center, recreation center, etc. The workers made 2,512 such trips in one day, which is 47 percent of all 5,319 trips. The workers made 40 percent of their total trips for work-purpose. For non-workers, we selected 3,545 trips (73 percent), out of 4,869 trips during one weekday.

From the sample of 1,971 respondents, we removed those trip-makers who's both survey days were weekends; who spent night outside of home (e.g. summer cottage, trailer, etc.) during survey period; did not own a car, and who worked at home (tele-workers). Also, we excluded a few respondents from the analysis who made a few, but extremely long-distance trips. We identified those respondents via two steps. First, we chose a maximum distance (30 km) to define *extreme* distances. We chose the 30 km cut-off because the distribution of all trip-distance revealed that around 97 percent trips were within 30 km. Also, Sackville, a major urban center, is located at around 30 km from downtown Halifax (Figure 2.1). It could be a typical behavior if someone took a leisure trip from Sackville to a downtown movie theatre. Anything beyond 30 km would be considered as atypical behavior. Next, we computed the total daily travel distance with and without the *extreme* (>30 km) distances for a person, and calculated the difference between the totals. The difference was below 10 km for over 98 percent of the respondents (worker and non-worker). We considered that the travel behavior of the remaining 2 percent of respondents as atypical. Thus, they were excluded them from the analysis. After several steps of data *cleaning*, we selected 1,196 respondents (577 workers and 619 non-workers) and 6,057 non-work trips for the analysis.

2.3.2.2 Built environment variables

We computed a comprehensive set of BE variables. As discussed in the previous section, studies represent the BE through different metrics of 3Ds (density, diversity, design) and different types of accessibility measures. Most studies compute the 3Ds near a respondent's home. Very few studies (such as, Frank et al., 2008; Maat and Timmermans, 2009) measure the BE around workers' workplaces. We computed BE near home and workplace[5], for workers. Also, we measured BE at two different scales – ¼ km and 1 km buffers (straight-line distance) around home and ½ km around workplace. We chose the ¼ km as it is used commonly in the literature (e.g., Boarnet and Sarmiento, 1998; Krizek and Waddell, 2002; Krizek, 2003). The 1 km buffer size was derived empirically. We explored the distribution of trip-distance and observed that more than 80 percent of walking trips were taken within 1 km (straight-line distance) from home. Thus, our data suggest that 1 km is representative of the walk-shed in HRM. For work-based walking trips, we found the walk-shed to be ½ km.

We computed the same set of BE variables (noted in the parenthesis if otherwise) for home and workplace. The 3D variables are: net residential density (near home); net

[5] *Workplace* corresponds to both *workplace* and *school*.

commercial density (near work);; entropy index; Herfindahl-Hirschman Index or HHI; ratio of four-way to all intersections; density of all intersections (per square km), and ratio of side-walk to road length. We also computed the ratio of building footprint and parcel area near workplace as proxy of parking space availability (Frank et al., 2010). The entropy index was calculated as:

$$Entropy = \{-\sum_k[(p_i)(\ln p_i)]\}/(\ln k), \quad (1)$$

Here, k is the number of land-use categories (residential, commercial, office, institutional, and park) within the buffer and p_i is the proportion of any land-use type. The HHI was computed using as:

$$\sum_i (P_i * 100)^2 \quad (2)$$

The notations are the same as in entropy index. We also calculated three types of accessibility measures (Scott and Horner, 2008) – gravity, proximity, and cumulative opportunity. We classified the opportunities as retail, service, religious, leisure, and active recreation, and computed three types of accessibility for each category. For any land-use opportunity-type, gravity accessibility was computed by:

$$A_i = \sum_j W_j \exp(-\beta d_{ij}), \quad (3)$$

Here, A_i is the gravity accessibility; W_j is the weight of opportunity j; β [6] is a distance decay parameter, and d_{ij} is the network distance from a respondent's home i to that particular opportunity j [7]. Since we computed the regional accessibility, all the opportunities were included in the formula. As for proximity, we computed the shortest network distance from a respondent's home and workplace to the aforementioned opportunities. We also computed the network distance from home and workplace to the closest bus stop, shortest distance to any shopping mall, employment centers (as per the STAR dataset there are 13 such centers) and large parks. The number of opportunities of an opportunity type gave the cumulative opportunity within the home and workplace buffer.

When the number of BE variables is high, like in this study, often they are combined through factor analysis (e.g., Cervero and Kockelman, 1997; Bagley and Mokhtarian, 2002; Krizek, 2003) and the factors are used in the model. However, we preferred to use the original variables because they are easy to interpret and would be intuitive to policy makers.

[6] The value of β was determined empirically. A regression model was run with distance of every trip destination from home as independent variable and natural logarithm of trip frequency as dependent variable. The model coefficient gave the value of β.

[7] Because we did not have employment information, we used building footprint area as a proxy of employment. For places like parks or playgrounds, the parcel area was used.

2.3.2.3 Control variables

We use three sets of control variables – socio-economic, attitude, and weather variables. The socio-economic variable set represents respondents' personal and household characteristics. It includes age; gender; work-duration and commute-duration (if worker); education status; immigrant or not; how long living in the current neighborhood; annual personal income; availability of bus pass; household size; number of vehicle in the household; number of vehicle per licensed people; number of children of age below 5, 6-10 and 11-15; number of seniors (age>65) in the household; type of household (couples without children, couples with children, single, single parent and other); number of workers in the household, and monthly cost of parking at work (if worker).Tables 2.1 and 2.2 present descriptive statistics of the variables which are significant in our models[8].

The attitude variables are included to control for the preference for residential location and travel mode. The STAR questionnaire asked more than 30 attitudinal questions. We did not find a strong correlation among them (*r*<0.6), but through Wilcoxon Signed Rank Tests we observed that some of the attitudinal variables were not significantly different from others. We only kept those variables that are representative of other variables. Most of them are dichotomous, the rest are 3-point scale responses. Sixteen attitude variables remained after the Wilcoxon Signed Rank Tests. They are: feeling safe to

[8] Due to space limitations we only display here the variables that are significant in our models. The descriptive stats of other variables are available upon request.

walk after dark; preference of neighborhood near work and recreation centers; preferred walking distance; preference of having store, drugstore, daycare, school, post office, club and park within walking distance; transit convenience, cheapness, safety and accessibility, and workaholic or not. The weather variables that we used are: daily amount of rain, snowfall and precipitation; minimum, maximum and mean temperatures; maximum gust; and amount of snow on the ground.

2.3.2.4 Model specifications

We use the following models:

$$Y_{PKT(OLS)} = \beta_0 + \beta_{SE}X_{SE} + \beta_{ATT}X_{ATT} + \beta_{WE}X_{WE} + \beta_{BE}X_{BE} + \varepsilon \quad (4)$$

$$Y_{PKT(LAG)} = \beta_0 + \beta_{LAG}WY_{PKT} + \beta_{SE}X_{SE} + \beta_{ATT}X_{ATT} + \beta_{WE}X_{WE} + \beta_{BE}X_{BE} + \varepsilon \quad (5)$$

Here, Y_{PKT} is daily personal vehicle kilometers travelled (PKT); X_{SE}, X_{ATT}, X_{WE} and X_{BE} are respectively the sets of socio-economic, attitude, weather and built environment variables, and their corresponding notations of βs are the coefficients. The first equation is the formulation of ordinary least square (OLS) regression while the second equation represents the spatial lag model. This model is used when one spatial observation is likely to be influenced by its neighboring observations, a phenomenon called *spatial autocorrelation*. We observed that both worker and non-worker PKT was spatially autocorrelated. The magnitude of autocorrelation was lower for worker PKT (Moran's I = 0.017) than that of non-worker PKT (Moran's I = 0.131), but both were significant (p<0.05). This violates the OLS assumption of independent error terms (ε). The spatial lag

Table 2.1: Descriptive statistics of selected variables (worker)

Variable	Mean	SD	Percent
PKT	11.81	14.24	
Work duration (hour)	6.77	2.23	
Male		0.50	50.09
No. of vehicle in the HH	1.86	0.74	
Household owner		0.20	70.71
Single		0.27	7.63
No. of worker in the HH	1.78	0.76	
Feel safe to walk after dark (moderate)		0.50	56.33
Peferred walking distance	18.23	8.17	
Preference of park within walking distance (moderate)		0.40	19.93
Preference of park within walking distance (high)		0.43	74.87
Total precipitation (mm)	4.08	9.29	
Shortest distance of any mall from home	4562.15	5466.57	
Ratio of four way to all intersection within 1 km of home	0.17	0.13	
Shortest distance of any restaurant from workplace	926.17	5105.35	
Ratio of building to parcel area in 500m of workplace	0.38	0.29	

Table 2.2: Some descriptive statistics of selected variables (non worker)

Variable	Mean	SD	Percent
PKT	25.08	23.18	
Male			43.13
Diploma			26.98
Income: 20,000 to 39,999			25.85
Income: 40,000 to 49,999			21.65
No. of vehicle in the HH	1.62	0.71	
Total snow	0.69	2.38	
Maximum temperature	12.22	10.06	
Entropy in 1 km buffer	0.54	0.13	
No. of active recreation centers in 1 km buffer	43.22	26.74	
Service gravity accessibility	350.12	151.30	

model tackles this problem by introducing a spatial lag variable, WY_{PKT}, where W is the standardized spatial weight $N \times N$ matrix (N=number of observations) with zero diagonal values, and β_{LAG} is the spatial lag parameter (Anselin, 1988). The spatial lag model is used when the behavior (PKT) of an observation is likely to be influenced by the behavior of its neighboring observations. Since travel is a derived demand, it is not practical to expect that PKT of a person is influenced by the neighbor's PKT. Their similar behavior is rather attributed to their similar residential location choice. We used OpenGeoDa 0.9.8.14 to compute both the spatial weight matrix and the spatial lag models[9]. We used distance weight setting the default minimum distance (approx. 10 km for workers and 8 km for non-workers) to allow at least one neighbor to every observation. Any lower threshold values could be used and that would reduce the spatial dependency of the neighbors. But, as will be evident in the results section, we did not find a big difference between OLS and the spatial lag models.

Our initial modeling approach was to use a Structural Equations Model (SEM). Our choice of dependent and independent variable sets is similar to that of Bagley and Mokhtarian (2002) who applied SEM to model trip distance by auto, transit, and walk trips against socio-economic, BE, and attitude variables. But, the travel behavior is different in our empirical context. Table 2.3 suggests that multiple modes of transport (here, auto and

[9] GeoDa is opensource software, available at http://geodacenter.asu.edu/software/downloads.

walking) are used by only 20 percent of workers and 23 percent of non-workers. We, therefore, chose not to use SEM to explain 20 percent of the travel behavior. Results

We made the decision to use the spatial lag model, instead of the spatial error model, based on the Lagrange Multiplier (LM) test of OLS. The LM test for lag was significant for both worker ($p<0.05$) and non-worker ($p<0.1$); but the ML test statistic for error was not.

Tables 2.4 and 2.5 report respectively the results of worker and non-worker personal vehicle kilometers travelled (PKT)[10]. Variables significant at the 90 percent significance level are presented. Along with the coefficient value and significance, we computed the elasticity of the interval or ratio-type variables using this formula (Ewing and Cervero, 2010):

$$elasticity = \beta * (\bar{x}/\bar{y}) \tag{6}$$

Here, β is the coefficient; $\bar{x}$ and $\bar{y}$ are respectively the average of independent variable and PKT.

[10] The distribution of worker and non-worker PKT are skewed. Therefore, two separate models were run by transforming both PKTs by natural logarithm. But, the R^2 of the log-transformed models were not higher than the models with original PKTs. Here, only the PKT models are reported.

Table 2.3: Mode interaction in one day, worker and non worker

Mode of transport	Worker		Non worker	
	Number of respondent	Percent	Number of respondent	Percent
A	348	60.3	450	72.7
AT	2	0.3	1	0.2
ATW	2	0.3	6	1.0
AW	112	19.4	141	22.8
TW	0	0.0	2	0.3
W	113	19.6	19	3.1
Total	577	100.00	619	100.00

A = Auto, T = Transit, W = Walking

2.3.3 Worker PKT

We model personal-vehicle kilometers traveled (PKT) during a weekday. As is seen from Table 2.4, the spatial lag variable (WY_{PKT}), that is Weight of PKT, is significant at the 90 percent confidence interval. The negative sign of the spatial lag coefficient suggests that the neighbors of any observation tend to reduce its PKT. But, the magnitude of the coefficient is very low. This is consistent with the fact that the improvement of the model R^2 from OLS to spatial lag model is miniscule (0.005). Recall from the previous section that the value of spatial autocorrelation of worker PKT is very small (Moran's I = 0.017), which is why model's explanatory power is not improved much by including the spatial lag variable (WY_{PKT}). However, for the sake of simplicity, only spatial lag models will be discussed.

Our modeling approach was to input the control variables, that is, respondents' socio-demographics, attitudes, and weather variables, and come up with a base model with significant control variables. We then entered the BE variables and observed the change in the model's explanatory power. If the inclusion of any BE variable made any control variable insignificant, we excluded that BE variable. Thus, the BE variables reported in the model have a *true* impact on worker PKT. The same procedure was used for the non-worker model.

The signs and even the magnitude (elasticity) of the control variables are intuitive. Work duration has the highest, negative impact on worker PKT. This makes sense as the

Table 2.4: Results of linear regression and spatial lag model (dependent variable: PKT by worker)

Variables	OLS			Spatial lag		
	Coef.	*t*-stat	Elasticity	Coef.	*t*-stat	Elasticity
Weight of PKT	NA	NA		-0.48	-1.68	
Constant	26.98	5.41		32.55	5.70	
Control variables						
Work duration (hour)	-0.79	-3.28	-0.45	-0.60	-2.47	-0.34
Male	1.97	1.81		2.56	2.34	
No. of vehicle in the HH	1.53	1.90	0.24	1.69	2.09	0.27
Household owner	-7.33	-2.66		-7.10	-2.53	
Single (reference: HH with child over 15 year)	5.51	2.56		6.09	2.81	
No. of worker in the HH	1.91	2.49	0.29	1.92	2.46	0.29
Feel safe to walk after dark (moderate)	-2.91	-2.64		-3.27	-2.94	
Preferred walking distance	-0.15	-2.30	-0.24	-0.14	-2.05	-0.21
Preference of park within walking distance (moderate)	-4.43	-1.67		-3.59	-1.35	
Preference of park within walking distance (high)	-5.54	-2.26		-4.69	-1.91	
Total precipitation	-0.07	-1.24	-0.02	-0.07	-1.26	-0.03
Built environment variables						
Shortest distance of any mall from home	0.00	2.11	0.09	0.00	2.60	0.13
Ratio of 4-way to all intersection within 1 km of home	-11.93	-2.66	-0.18	-14.43	-3.18	-0.21
Shortest distance of any restaurant from workplace	0.00	5.12	0.02	0.00	2.55	0.02
Ratio of building to parcel area in ½ km of workplace	-3.57	-1.67	-0.11	-7.96	-4.10	-0.26
Model summary						
Model with control variables						
R^2		0.111			0.113	
Log likelihood		NA			-2316.172	
Model with control and home-BE variables						
R^2		0.157			0.157	
Log likelihood		NA			-2304.221	
Model with control, home-BE and workplace-BE variables						
R^2		0.181			0.186	
Log likelihood		NA			-2291.774	
N	577					

workers spend, on average, 7 hours at work (Table 2.1), which puts a time constraint on their travel. The second-highest value of elasticity is number of workers in the household, which tends to increase worker PKT. This is probably because a single-worker household has the freedom to choose its residence near opportunities as opposed to a two-worker household which might choose to locate somewhere in the middle of the two workplaces. Also, the more vehicles respondents' households own, the farther they travel. Males drive farther than females; tenants make longer trips than household-owners, and respondents who live alone travel farther than those who live with a partner and children.

We found some of the attitude variables significant in the worker PKT model. People, who prefer to walk farther, travel a shorter distance by car. Respondents, who feel comfortable to walk after dark, do the same. This variable might be a proxy for walkable neighborhoods. People who want to live near parks travel less distance. Interestingly, the moderate preference to live near parks became insignificant when the spatial lag effect was included. We did not find any effect of weather on non-work trip distance by auto. The weather variable closest to significance is total precipitation.

As mentioned before, we did not combine the BE variables through factor analysis. When putting the BE variables in the base model (model with significant control variables), we entered one BE variable from a BE group. For example, we computed the proximity of different opportunity categories (retail, service, recreation, etc.) from home. These variables are highly correlated (r>0.9) among themselves, thus the proximity variables belong to the same BE group. We entered the BE variable from a BE group that had the highest correlation with PKT. If any BE variable from its BE group was not significant, we tried other BE members of its group. But, for both the worker and non-worker models, we did not find any member of a BE group to be significant if its *best member* (the one with highest correlation with PKT) was not significant. After obtaining the final model with significant BE and control variables, we performed some iterations by replacing the *best member* of a group by other members and we chose the model with the highest R^2.

As can be seen from Table 2.4, four BE variables impact worker PKT. As expected, both home-based and work-based BE variables appear to be significant. Also, they display intuitive signs. For example, the shortest distance of any shopping mall from home is positively related to PKT. The proximity of a restaurant from workplace has a similar effect. This is no surprise because many workers make eating-out trips during their work hours. Workers, who live in a neighborhood with a grid-pattern road, travel shorter distances than those living in a neighborhood with curvilinear or cul-de-sac roads. The latter is a typical picture of a suburb. Also, the availability of parking space (ratio of building to parcel area) near work has a negative influence on PKT. This variable has the highest value of elasticity (-0.26) among the BE variables. The value indicates that a 10 percent increase in the ratio of building to parcel area near the workplace would reduce worker PKT by 2.6 percent. As opposed to many studies, we do not find any effect of residential or commercial density. This proves the claim and findings of some researchers (e.g. Kockelman, 1997) that density works a surrogate of other BE variables; when they are accounted for, density becomes irrelevant.

Table 2.4 also presents the relative contributions of control variables and BE variables to the model's explanatory power. The inclusion of home BE variables improved the model R^2 from 0.113 to 0.157. The work BE variables further improved the R^2 to 0.186. Overall, the BE variables increased the explanatory power of the model by 7.3 percent.

2.3.4 Non-worker PKT

The difference in R^2 between OLS and the spatial lag model for non-worker PKT indicates a very interesting phenomenon (Table 2.5). For the base model (model with control variables only), the R^2 is simply doubled when the spatial lag effect is accounted for. Interestingly, the R^2 virtually does not change in the final model (model with control and BE variables) after the inclusion of the spatial lag variable. Also, the Weight of PKT is not significant in the final model, suggesting no autocorrelation of the error term in the final model. Recall from Section 3.2 that non-worker PKT is highly autocorrelated (Moran's I = 0.131). The plausible explanation for the elimination of spatial lag effect in the final OLS model is that the BE variables in the model take care of the autocorrelation. This is an interesting finding that if proper BE measures are controlled for in a model of a spatially-varying dependent variable, the BE variables might tackle the autocorrelation problem. For such models, the OLS would suffice.

We applied the same modeling approach as discussed in the previous sub-section. Like workers, non-worker males travel farther than females. Interestingly, non-workers

Table 2.5: Results of linear regression and spatial lag model (dependent variable: non-worker PKT)

Variables	OLS			Spatial lag		
	Coeff.	t-stat	Elasticity	Coeff.	t-stat	Elasticity
Weight of PKT	NA	NA		0.22	1.44	
Constant	49.33	10.03		41.16	5.67	
Control variables						
Male	3.95	2.31		4.18	2.48	
Education: diploma (reference: high school)	-3.78	-2.00		-3.78	-2.02	
Income: 20,000 to 39,999 (reference: <20,000)	3.27	1.62		3.49	1.75	
Income: 40,000 to 49,999	3.71	1.71		4.01	1.86	
No. of vehicle in the HH	2.11	1.69	0.14	2.06	1.67	0.13
Amount of snowfall	-0.98	-2.59	-0.03	-0.97	-2.60	-0.03
Maximum temperature	-0.19	-2.05	-0.09	-0.20	-2.25	-0.10
Built environment variables						
Entropy within 1 km of home	-20.56	-2.47	-0.44	-21.56	-2.63	-0.47
No. of active recreation centers within 1 km of home	-0.11	-2.71	-0.18	-0.09	-2.42	-0.16
Service gravity accessibility	-0.00	-4.65	-0.45	-0.00	-2.66	-0.33
Model summary						
Model with control variables						
R^2		0.083			0.166	
Log likelihood		NA			-2755.211	
Model with control and home BE variables						
R^2		0.217			0.218	
Log likelihood		NA			-2732.731	
N	619					

with a diploma degree drive shorter distances than those having high school education. As personal income increases, so too does a non-worker's auto distance. We could not compute household income per person because the income data were categorical and total household income would be biased to household size. Like worker, non-workers travel more distance by car if their households own more vehicles. Unlike the worker PKT model, we find a significant constraining impact of harsh weather (snowfall and maximum temperature). Surprisingly, we did not find any attitude variable significant. We ran a separate model with only the attitude variables and found one statistically significant variable – high preference of living near a park, which when put into the model with the socio-economic variables, became insignificant.

There are three significant BE variables in the non-worker PKT model. Two of them are accessibility measures – service gravity, and cumulative opportunities of active recreation (playground, gym, etc.). Land-use diversity, measured by the entropy index, is also highly significant and has a negative influence on auto distance. The entropy index for a ¼ km buffer was also significant, but with a much lower coefficient value. This indicates to the problem of choosing an arbitrary scale of BE measurement and suggests that the buffer size should be empirically derived (please see section 3). We also experimented with different entropy measures by varying the land-use categories in the formula. The choice of correct land-use categories is crucial for this index. For example, a mix of residence and retail is better than that of agricultural and residential uses (Krizek, 2003). We computed three entropy measures. The land-use categories for the first index were residential, commercial, office, institutional, industry, and park. The second index excluded industry and the third also left out park. Industry was excluded because it does not attract non-work trips. Also, we wanted to test if park had any *size-bias* making the entropy index inefficient. Since park-parcels are relatively larger than those of residential or commercial and entropy computation is based on area, we suspected potential *size-bias* leading to an underestimated index. But, we found that the entropy with park and without industry was statistically significant in the model.

Since there is no significant attitude variable in non-worker PKT model, it is important to discuss whether in this model the BE-PKT relation is *causal* or not. It is possible that the STAR questionnaire survey did not ask the *right* questions to capture non-workers' attitudes. This is one of the drawbacks of using attitude variables to control for residential self-selection (Cao et al., 2009a). If this is the case, the BE variable parameters may be overestimated in this model. On the other hand, most studies that accounted for residential self-section through various methods generally found that the role of self-selection is much smaller than that of BE. Some studies (e.g., Khattak and Rodriguez, 2005) even found no influence of attitude variables on TB. Our understanding on this regard is that if we had a very well-defined set of attitudinal variables, their effect would be still trivial. We included 11 variables pertaining to residential choice and 5 variables on transport mode (transit and walk) preference in our model. This set of attitude variable should comprise a major area of the *universal set* of all possible attitudinal questions.

Therefore, based on the literature on self-selection and our reasoning, we infer that the BE coefficients of the non-worker PKT model might be overestimated, but not by much.

As was evident with the worker PKT model, this model is also improved by the inclusion of BE variables. Although the spatial lag parameter is not significant in the non-worker PKT model, the use of spatial lag model provides a benefit. This is the reason: comparing the OLS R^2 of the base model (control variables only) and the final model (BE variables included), one would observe a resounding 13 percent improvement of R^2 by BE. This is untrue, because the OLS estimates of the base model are inconsistent since the model violates the assumption of independent error terms. The spatial lag model gives the accurate R^2 value and BE genuinely improves the model by 5.2 percent. To compare, BE variables explain more variation (7.3 percent) of worker PKT. This is reasonable because workers have more time constraints during weekdays; thus their TB concurs more with BE.

2.4 Conclusion

The purpose of this chapter was to examine the effect of BE on people's auto travel distance. We model a subset of overall travel (47 percent and 73 percent of all trips made by worker and non-worker, respectively) and find a strong influence of BE when self-selection is accounted for. This suggests an important finding, which is, BE impacts certain type of trips. When examining the TB-BE link, future research should categorize a person's overall travel and model these categories through a system of equations, say, Structural Equations Modeling (SEM). One might find that BE has a stronger influence on some maintenance and discretionary trips while household structure explains certain subsistence trips (such as, drop-off or pick-up). Some recent work (Maat and Timmermans, 2009; Pinjari et al., 2009; Lee et al., 2009; Kang and Scott, 2010) adopt a similar approach, but with activities. They classify activities in three types – subsistence, maintenance and discretionary and investigate the influence of different sets of variables (BE, socio-demographics, etc.) on different activity-types.

We also observe an interesting phenomenon when applying the spatial lag model. The inclusion of proper BE variables can tackle the spatial autocorrelation effect. This was evident in our non-worker PKT model. Thus, OLS could be sufficient to produce consistent estimates of BE. Still, we suggest the use of a spatial autoregressive model (lag or error whichever appropriate) to truly capture the R^2contribution of BE, because OLS might produce inconsistent estimates in control-variable models and underestimate the contribution of control variables to model R^2.

This study has two limitations. First, the attitude variables included in the model might not be sufficient to represent residential and travel mode preference. Readers should be cautious when interpreting the elasticity of BE variables in the non-worker PKT model. The absence of significant attitude variables and higher BE elasticity indicates *endogeneity* bias in the model. Future studies using STAR dataset might consider adopting other methods to control for residential self-selection. Two possible methods could be employed: use of instrument variables and a joint model of residential location and TB. The use of instrumental variables might be difficult when buffers are used to measure BE since all the non-BE information are available at aggregate (census tract) level. For example, the data on ethnicity are not available in a person's buffer area, its available in a census tract. Modeling residential location and travel behavior simultaneously might be a better option to control for residential self-selection.

The second limitation is that we chose to model only auto-travel and leave out transit and walk distance. Their inclusion through SEM or seemingly unrelated regression would provide a better understanding of the process. Nonetheless, the method we use allows us to employ spatial lag model and provides an interesting finding that the inclusion of proper BE variables can handle spatial autocorrelation problem.

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3 Is trip chaining a desirable travel behavior? An investigation from the built environment perspective

3.1 Introduction

When a trip-maker travels from home (or workplace) to multiple destinations by linking two or more trips before returning to home (or workplace), the journey is called a trip chain. Trip chaining is a response to the increasing time constraints that individuals are now facing, especially in urban areas (Recker et al., 2001).Due to the growing need to spend more time at work, growth of multi-worker households, improvement of affordability and taste for particular commodities, amongst other reasons, trip chaining has become a common trait of urban travel behavior (Donaghy et al., 2004; Hensher and Reyes, 2000).

A number of studies have been conducted to obtain a better grasp of trip chaining behavior. Figure 3.1 is a simple schematic representation of the factors that are hypothesized to influence trip chaining. How many stops (or trips) are made in a tour (or trip chain) is a measure of how complex the tour is. Factors that influence tour complexity can be grouped as personal and household attributes, choice of travel mode, built environment, preference for certain travel or residential location, and other tour-specific attributes. For instance, a working woman may drop her kids to daycare en route to work (link 1 in Figure 3.1) and for that auto is a convenient mode (links 2 and 4). High-income earners may chain their shopping trips (link 5, tour purpose) to multiple stores to buy

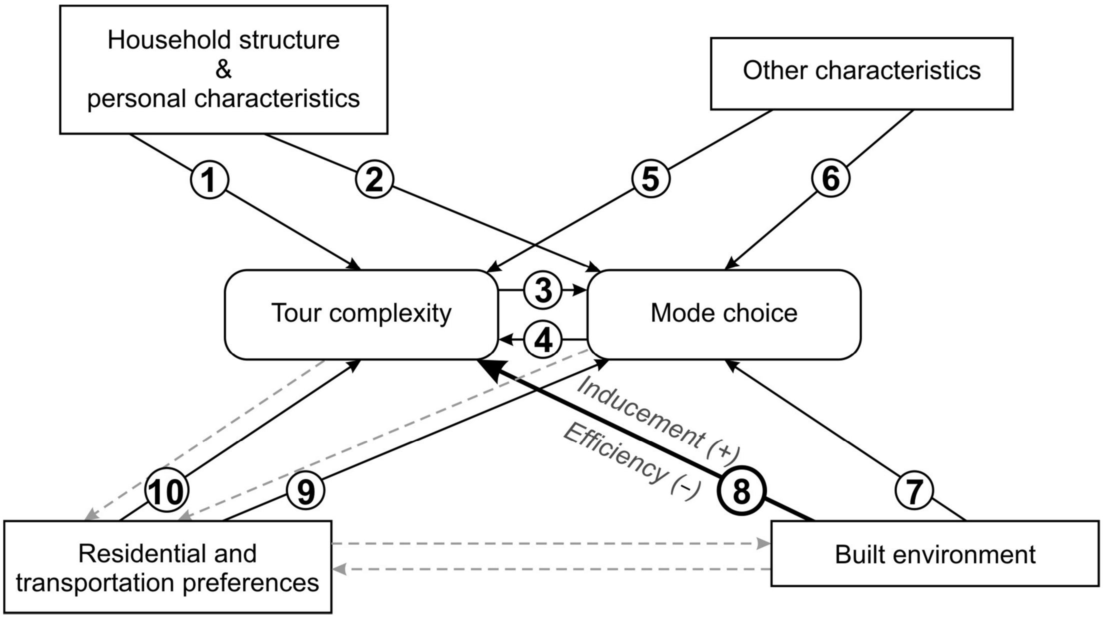

Figure 3.1: Factors that affect tour complexity

particular goods of their choice. Suburban commuters may find it convenient to make a few stops for shopping on the way home from work because goods and services are located away from their home (link 8). Also, some people who like to reside in a quiet neighborhood in a suburb may also like to travel by car to optimize their travel by trip chaining (links 9 and 10). Over time, as Handy et al. (2005) argue, travel behavior and the built environment can also change someone's preferences for certain travel and neighborhood type (dotted links in Figure 3.1). These relationships are discussed at length in the following section. The focus of this study, however, is the link between built environment (BE) and tour complexity (link 8). Below, we explain why.

Trip chaining results in more efficient utilization of road space because it reduces the number of return trips. Thus, apparently, it could be considered as desirable travel behavior from a transportation planning perspective. However, findings from a number of studies suggest the contrary. First, when a commute trip is chained with non-work stops, it deteriorates peak-hour traffic congestion (Ye, Pendyala and Gottardi 2007). Second, trip chaining results in more challenges to TDM measures to promote public transit because auto-users find trip chaining more convenient due to more flexibility and speed than transit users (Bhat, 1997; Chen et al., 2008). Third, it is hypothesized and there is some empirical evidence to suggest that people living in less accessible areas tend to link their trips in order to optimize their out-of-home activities (Krizek, 2003a). If this is the case, then trip chaining would be a big challenge for any TDM strategy based on land-use planning. However, Cao et al. (2008) contend that the BE could have an opposite effect on trip chaining, that is higher accessibility might *induce* a traveller to make more stops. Also, some researchers contend that the BE has very little or nothing to do with trip chaining (Kitamura et al., 2001).

So far, our understanding on the relation between the BE and trip chaining is not clear. We cannot say with certainty whether or not compact development will *induce* more trips or reduce the need for trip chaining or even if there will be any significant impact of BE at all. This study, therefore, investigates what impact (if any) the BE has on trip chaining. Most studies (except Cao et al., 2008) on the BE – trip chaining relation do not control for residential self-selection which leaves the BE parameters prone to endogeneity bias (Mokhtarian and Cao, 2008). We address this issue by including attitudinal variables in our models. In other words, we focus on the BE – trip chaining relation (link 8 in Figure 3.1) while all other links (except link 3) are accounted for.

The next section briefly outlines the literature, especially what factors are observed to have influence on trip chaining behavior. The following section describes the data, variables and statistical models used in this study. The results are described in the subsequent section followed by conclusion.

3.2 Literature review

Trip chaining is the aspect of travel behavior that has received the least attention with respect to the BE. Most empirical research on travel and the BE has focused on other travel aspects such as trip generation, travel distance, mode choice, and auto ownership (Ewing and Cervero, 2010).

Almost every study on trip chaining has examined the effect of household and personal characteristics (link 1 in Figure 3.1) on trip chaining behavior. For instance, in multi-worker households, the female-workers tend to chain their commute trips with non-work trips indicating the higher household responsibilities of females (McGuckin and Murakami, 1999). Strathman et al. (1994) observe that having one or more preschoolers in the household increases the chances of making complex work tours. They also find that compared to traditional households with two or more adults, single parents make more non-work stops when returning from work. This is a response to higher responsibilities of single parents than other adults. Similar effects are observed by Thomas and Noland (2005) – with an increase in household size, tour complexity decreases since other members share household responsibilities. Further, households with higher incomes make more complex tours, which might be attributed to the greater shopping ability and/or higher degree of activity participation (Maat and Timmermans, 2006).

A lot of studies focus on understanding the mode choice behavior of chained trips (links 3 and 4 in Figure 3.1). Promoting public transit and non-motorized modes of transportation have been some of the most analyzed TDM instruments (Wallace et al., 2000) and with the increasing rate of trip chaining practice in North America and Europe (Donaghy et al., 2004), researchers have shown interest in exploring the effect of trip chaining on travel mode choice. Bhat (1997), for example, investigates the relation between commute mode choice and the number of non-work stops when returning home from work. Using a joint multinomial logit and ordered response formulation, he observes that solo-auto users make the most non-work stops while commuting. He demonstrates that an improvement in transit service might entice the solo-auto users, who make simple tours, towards transit. However, solo-auto users, who make complex tours, are less likely to change their commuting mode. Hensher and Reyes (2000) and Chen et al. (2008) notice a similar behavioral pattern. In the context of Sydney, Australia, Hensher and Reyes (2000) model different categories of tours (simple, complex, non-work, work) and modes (auto and transit). Using multinomial logit and nested logit techniques, they find for all tour-types that as tour complexity increases, reliance on cars increases and that on transit decreases. Modeling the auto ownership and propensity to use auto in a tour, Chen et al. (2008) draw a similar conclusion – as the number of stops in tour increases, the propensity to use auto increases.

An interesting work is undertaken by Ye et al.(2007) regarding the relation between mode choice and trip chaining. They explore three hypotheses – trip chaining decision precedes mode choice, follows mode choice, and the two decisions are made simultaneously. Although they notice the causality to be bidirectional; they find the model structure in which tour complexity drives mode choice is the most significant. However, in all three models, the results indicate that if individuals are forced to take a complex tours, they are likely to choose car for the tour. The positive association of auto-usage and trip chaining can be explained by the higher degree of flexibility offered by auto to schedule out-of-home activities. Also, as a faster mode, auto provides additional time to make more stops (Frank et al., 2008).

The relation of trip chaining with the BE is not as straight forward as it is with household structure and travel mode. The literature puts forward a variety of findings when answering the question: "How does BE influence trip chaining behavior?" It is hypothesized that people who live and work in poorly accessible areas make complex tours in order to make efficient utilization of their out-of-home time use. On the other hand, ceteris paribus, people who live closer to opportunities do not have to be as careful when scheduling out-of-home activities. If they miss buying something, for instance, they can just go out and do it, since the services are close by. This leads to another hypothesis: people, who live in high-accessibility neighborhoods, make more frequent tours. Crane (1996) and Krizek (2003b) confirm the second hypothesis. Thomas and Noland(2005)corroborate with the first hypothesis that density has a negative effect on tour complexity, but refute the findings of Crane (1996) and Krizek (2003b) that high density increases tour frequency. Cao et al. (2008) refer to the effect described in the first hypothesis as the "efficiency" effect since the residents of suburbs tend to efficiently utilize their travel by chaining trips. They also observe an opposite effect of BE on trip chaining – what they call the "inducement" effect. Their results suggest that respondents who prefer to live closer to opportunities make more stops. On the contrary, people who prefer to minimize travel make more stops ("efficiency" effect). However, most studies do not report the *inducement* effect. For example, while examining household tour complexity, Krizek (2003a) finds that households living in highly accessible areas make simple but more frequent tours. Wallace et al. (2000) also observe similar phenomena in their study – tours originating in the CBD are simpler. They explain that in the CBD more opportunities are concentrated, thus the traveler does not need to schedule complex tours. An early study by Golob (2000) on trip chaining – BE relation within an activity-based modeling framework draws similar conclusions. Golob (2000) develops a Structural Equations Modeling (SEM) framework to model out-of-home activity duration, travel time ,and generation of different types of tours (work, non-work, simple, and complex). His model suggests that as accessibility increases the generation of both simple and complex tours increases but the effect is stronger for simple tour-generation.

More recently, similar efforts have been made to explain several travel aspects along with trip chaining. Applying several independent regressions, Maat and Timmermans (2006) examine the influence of the BE on activity participation, tour complexity, and travel distance. The study provides some interesting findings. First, density is positively related to tour complexity (average number of trips per tour) which probably indicates to the *induced* trip chaining explained by Cao et al. (2008). This is contrasted by the results of a second model (percent of complex tours). The model suggests that people living in suburbs are more likely to make complex tours which might be attributed to the *efficiency* effect. Frank et al. (2008) look at the impact of the BE on both trip chaining and mode choice. Using a nested logit model they find that high density, mixed land use, and a grid street network near home and work increases the use of walking and transit, compared to auto. Also, increased opportunities near home and work reduce the number of stops in the commute and midday work-based non-work tours.

Although attempts have been made to understand the impact of the BE on trip chaining behavior, very few studies account for the residential self-selection effect (an exception is Cao et al (2008) who analyze links 7 and 8), which makes the BE coefficients prone to overestimation (Mokhtarian and Cao, 2008). Besides, most studies (except Frank et al., 2008) represent the BE through one or two crude measures, like density, aggregate accessibility, or location of the household (CBD or suburb). The first limitation questions the consistency of BE estimates while the second one does not offer enough information on the BE – trip chaining relation to policy makers. The current study addresses both issues.

3.3 Data and methods

3.3.1 Data sources

The study area, the Halifax Regional Municipality (HRM), is a county located in Nova Scotia, Canada (Figure 3.2). The tour data for this study are obtained from Halifax Space – Time Activity Research (STAR) project, conducted between April 2007 and May 2008. The time-use diary of the Halifax STAR dataset contains two-day activity information of 1,971 respondents age 15 years and older who were selected from 1,971 randomly chosen households. The diary contains the time, locations (fixed locations and travel modes), along with several other attributes of each activity performed in 48 hours by the respondents. The location of each activity was recorded through a GPS (Global Positioning System) device that the respondents carried throughout the survey period. The STAR dataset “represents the world’s largest deployment of global positioning systems (GPS) technology for a household activity survey to date” (Spinney and Millward, 2010 p. 134).

The household information and other socio-demographics came from the STAR household questionnaire survey. The respondents also completed more than 30 attitudinal questions (elaborated later in this section). The built environment data are collected from the STAR Land Use (parcel level) dataset; a 2008 DMTI Network Dataset; a 2006 Building Footprint and Sidewalk Dataset 2006 obtained from the HRM department of Planning and Development Services, and 2006 Census of Canada data. In addition, meteorological information of each day of entire survey period was collected from Environment Canada website[11].

[11] http://www.climate.weatheroffice.gc.ca/climateData/hourlydata_e.html?Prov=NS&StationID=6358&Year=2007&Month=4&Day=1&timeframe=1

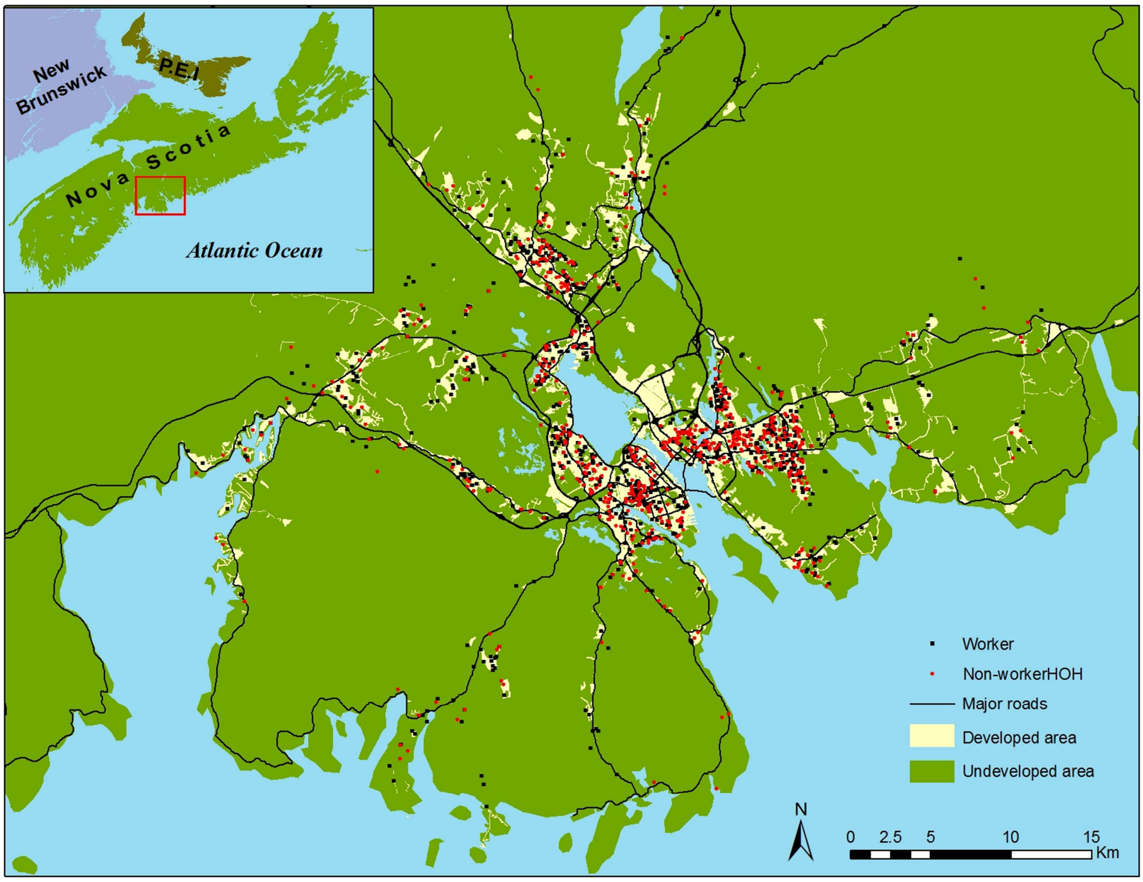

Figure 3.2: A part of Halifax Regional Municipality displaying all respondents' (worker and non-worker) home locations

3.3.2 Variables

3.3.2.1 Tour complexity

In this study, we defined a tour or a trip chain based on two anchors – home and workplace. When a journey is started from home (or work) and ends at home (or work), a tour is completed. A similar formulation of tour is adopted by McGuckin and Murakami (1999) and Frank et al. (2008). Some studies (Hensher and Reyes, 2000; Ye et al., 2007) use only home as an anchor to define a tour. Others include additional anchors along with home and workplace. For example, Wallace et al. (2000) consider any destination to be an anchor if the traveler spent more than 90 minutes there. The 90 minute cut-off is decided based on the distribution of duration of out-of-home activities. However, we consider home (and workplace for workers) as the center of all activities where people spend the greatest amount of time every day. Other places in their activity space are where they go occasionally to fulfill certain needs (shopping, leisure, socialize, etc.).

Based on two anchors, we identified three types of tours – home to other places then back home (HOH); home to work[12] or work to home (HW/WH); and work to other places, then back to work (WOW). By definition, a worker can perform all three types of tours while a non-worker can undertake only HOH tours.

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[12] *Work* corresponds to both *work* and *school*.

Before aggregating trips into tours, we removed trips without any destination, that is, trips taken only for the sake of travel (jogging, pleasure drive, etc.). Also, the multimodal trips in a tour (e.g., home-walk-bus stop-bus-walk-work) were counted as one trip, that is, the intermediate stops were ignored. We only included weekday travel for the analysis. This is because the purpose of the study is to understand the relation between the BE and trip chaining; and we expect this association to be stronger on weekdays due to greater time constraints and a higher degree of roadway congestion than on weekends. We focused the analysis to one-day travel because the survey days of many respondents comprised both weekday and weekends. If both survey days were weekdays, we included the day the respondent made the most trips in order to obtain a larger sample of travel. Since this procedure was applied to all respondents with two weekdays, the sample is not biased towards more trip-makers. Also, we removed the respondents who worked at home.

The unit of analysis in most studies is the tour itself (Chen et al., 2008; Frank et al., 2008; Ye et al., 2007). There is a benefit to tour-based modeling. It allows the researcher to include tour-specific variables, such as time of day to control for roadway congestion, tour purpose, tour mode choice, amongst others. However, we contend that individuals schedule their activities for the whole day. Treating each tour as an individual unit would not be behaviorally prudent. Thus, our unit of analysis is the person and it goes with our research question – How does the BE influence a *person's* trip chaining behavior? The metric we chose for tour complexity is average number of trips per tour in a day. Table 3.1 shows the average complexity of different types of tours.

Table 3.1: Average weekday tour complexity of workers and non-workers. The values shown correspond to number of respondents

	Non-worker	Worker		
Average trips per tour	HOH	HW / WH	HOH	WOW
1.00		242		
1.01 - 2.00	108	402	232	255
2.01 - 3.00	230	149	151	80
3.01 - 4.00	159	61	58	15
4.01 - 5.00	67	15	36	9
5.01 - 6.00	30	2	11	1
6.01 - 7.00	21	2	4	1
7.01 - 8.00	12	1	2	1
8.01 - 9.00	2	0	5	1
9.01 - 10.00	4	1	1	0
10+	5	1	2	2
Total	638	876	502	365

3.3.2.2 Built environment variables

We computed a comprehensive set of BE variables. We measured the variables at two different scales – ¼ km and 1 km straight line buffers around the home and ½ km buffer around the workplace. The ¼ km is used commonly in the literature (Boarnet and Sarmiento, 1998; Krizek and Waddell, 2002). The 1 km scale was derived from the distribution of home-based walking trip distance where more than 80 percent of trips were within 1 km from home. This indicates that 1 km defines the walk-shed in HRM. We found the walk-shed to be ½ km around workplace.

The BE variables can be classified in two categories – 3D variables (density, diversity, and design) and accessibility variables. In addition, we included the distance to work from home through the network. The 3Ds consist of two density variables – net residential density (near home only) and net commercial density (near work only). Variables for land-use diversity are – the entropy index and Herfindahl-Hirschman Index. Three variables were computed to represent street design – ratio of four-way to all intersections, density of all intersections (per square km), and ratio of side-walk to road length. In addition, the ratio of building footprint and parcel area near workplace was computed as a proxy measure of parking space availability (Frank et al., 2010). The mathematical formulation for entropy index is

$$Entropy = \{-\sum_k [(p_i)(\ln p_i)]\}/(\ln k) \quad (1)$$

Here, k is the number of land-use categories (residential, commercial, office, institutional, and park) within the buffer and p_i is the proportion of any land-use type. The Herfindahl-Hirschman Index was computed using this formula

$$\sum_i (P_i * 100)^2 \tag{2}$$

The notations are the same as in entropy index. The second category of BE variables comprise three types of accessibility (Scott and Horner, 2008). They are: gravity, proximity and cumulative accessibility of five types of opportunities– retail, service, religious, leisure, and active recreation. For any category, the gravity accessibility is

$$A_i = \sum_j W_j \exp(-\beta d_{ij}) \tag{3}$$

Here, A_i is the gravity accessibility; W_j is the weight of opportunity j; β is a distance decay parameter, and d_{ij} is the network distance from the respondent's home i to that particular opportunity j. As for proximity, we computed the shortest network distance from a respondent's home and workplace to the aforementioned opportunities. In addition, proximity of bus-stops from home and workplace were measured. The cumulative accessibility is the number of opportunities of an opportunity category within the home and workplace buffers.

Many researchers combine the BE variables through factor analysis in order to avoid the multicollinearity problem in the model (Bagley and Mokhtarian, 2002; Cervero and Kockelman, 1997). We used the original variables because they are easy to interpret and intuitive to policy makers.

3.3.2.3 Control variables

The control variables used are: socio-demographics, attitude, weather variables, time-related variables, and mode-choice. The socio-demographic attributes consist of household structure and personal characteristics. The variables are age; gender; educational status; immigrant or not; neighborhood tenure; annual personal income; availability of bus pass; household size; number of vehicles in the household; number of vehicles per licensed persons; number of children of age less than or equal to 5, 6-10, and 11-15; number of seniors (age>65) in the household; type of household (couples without children, couples with children, single, single parent and usual households, that is, households with two or more adults); number of workers and school-goers in the household, and monthly cost of parking at work (if worker). Tables 3.2 through 3.5 display some descriptive statistics of selected variables[13].

We control for residential self-selection by including attitude variables in the models. The variables represent preferences towards residential location and travel mode. The Halifax STAR questionnaire survey had more than 30 attitudinal questions. A

[13] Due to space limitations we only display here the variables that are significant in our models. The descriptive statistics of other variables are available upon request.

preliminary analysis did not reveal strong correlation among them (r<0.6), but through Wilcoxon Signed Rank tests we observed that some of the attitudinal variables were not significantly different from others. We selected those variables that are representative of others and deemed to have important policy implications. Most variables are dichotomous and the rest are 3-point scale responses. Sixteen attitude variables remained after Wilcoxon Signed Rank tests. They are: feeling safe to walk after dark; preference of neighborhood near work and recreation centers; preferred walking distance; preference of having store, drugstore, daycare, school, post office, club, and park within walking distance; transit convenience, cheapness, safety and accessibility; and workaholic or not.

We tested the importance of eight meteorological variables – daily amount of rain, snowfall and precipitation; minimum, maximum and mean temperature; maximum gust; and amount of snow on the ground.

The time-related variables are work-duration and commute duration (if worker), day of the week and month. We hypothesize that work and commute duration would induce a worker to undertake complex tours. We expect that people would make complex tours on Friday so that they do not have to go out on weekends. Thus, Friday was kept as a reference in the model. Also, we tested seasonal variations of tour complexity. January was the reference month and our anticipation was to observe more complex tours during spring and summer, compared to winter. Tour-specific variables are the modes a person chose to take all tours of specific type. If the workers did all HW/WH tours by auto, their *PersonMode* is auto for HW/WH tours. We assigned the main mode of a tour according to

Table 3.2: Descriptive statistics of selected non-worker variables for HOH tours

Variable	Description	Mean	SD	Percent
HOHComplexity	Average trip per home-other-home (HOH) tour	3.59	1.68	
PersonMode	Major mode used in all tours of the day			
Auto(ref.)	1 if auto is the main mode of all tours, 0 otherwise			82.13
Transit	1 if transit is the main mode of all tours, 0 otherwise			6.27
Walk	1 if all tours are taken by walking, 0 otherwise			2.51
OtherHOH	1 if the tours are taken by different modes, 0 otherwise			9.09
Weekday	Survey day			
Friday (ref.)	1 if Friday, 0 otherwise			20.38
Monday	1 if Monday, 0 otherwise			26.49
Male	1 if male, 0 if female			42.16
HHstructure	Structure of household			
UsualHH (ref.)	1 if the household has two of more adults and no child(ren) of age<16, 0 otherwise			
SingleParent	1 if the respondent is a single parent, 0 otherwise			1.10
HHworker2	Number of worker in the household	0.74	0.87	73.98
HHschoolgoer	Number of schoolgoer (age>15) in the household	0.14	0.41	14.42
SafeWalk	Feeling of safety to walk after dark			
SafeWalk_low (ref.)	Does not feel very safe			11.60
SafeWalk_med	Feels moderately safe			50.94
RegMalls_Hm	Shortest distance from home to regional malls	6.50	6.37	
Entropy4_1000	Entropy in 1 km from home, computed with four land-use categories	0.44	0.14	

Table 3.3: Descriptive statistics of selected worker variables for HOH tours

Variable	Description	Mean	SD	Percent
HOHComplexity	Average trip per home-other-home (HOH) tour	2.95	1.51	
PersonMode	Major mode used in all HOH tours of the day			
Auto (ref.)	1 if auto is the main mode of all tours, 0 otherwise			88.25
Transit	1 if transit is the main mode of all tours, 0 otherwise			2.79
Walk	1 if all tours are taken by walking, 0 otherwise			6.37
Weekday	Survey day			
friday (ref.)	1 if Friday, 0 otherwise			20.52
monday	1 if Monday, 0 otherwise			19.72
Health	Self-reported health status			
HealthPoor	Poor health condition			1.00
HealthGood	Good health condition			21.31
daycare	Preference of having daycare near home			
daycare_high (ref.)	High preference			22.71
daycare_low	Low preference			47.81
PostOffice	Preference of having post office near home			
PO_high (ref.)	High preference			12.35
PO_low	Low preference			34.06
PO_med	Moderate preference			53.19
entropy5_400	Entropy in 400m from home, computed with five land-use categories	0.39	0.17	
SWperArea_Wk	Sidewalk length per square km in 500m from workplace	9.04	9.58	

Table 3.4: Descriptive statistics of selected worker variables for HW/WH tours

Variable	Description	Mean	SD	Percent
HWComplexity	Average trip per home-work/work-home (HW/WH) tour	1.92	1.04	
PersonMode	Major mode used in all HW/WH tours of the day			
Auto (ref.)	1 if auto is the main mode of all tours, 0 otherwise			83.90
Walk	1 if all tours are taken by walking, 0 otherwise			4.00
HOH_Tour	1 if any HOH tour is taken during the survey day, 0 otherwise			57.31
WorkDuration_hr	Work duration in hour	7.02	2.37	
BusPass	1 if the person has a bus pass, 0 otherwise			7.20
HHstructure	Structure of household			
UsualHH (ref.)	1 if the household has two of more adults and no child(ren) of age<16, 0 otherwise			
Couple_kid	1 if the household comprise a couple and child(ren) of age<16, 0 otherwise			35.50
SingleParent	1 if the respondent is a single parent, 0 otherwise			2.97
Income	Annual personal income			
Inc_above100 (ref.)	1 if Income ≥ $100,000, 0 otherwise			9.47
Inc_below20	1 if Income < $20,000, 0 otherwise			8.90
Inc_20to40	1 if $20,000 ≤ Income < $40,000, 0 otherwise			19.86
Weekday	Survey day			
Friday (ref.)	1 if Friday, 0 otherwise			19.86
Monday	1 if Monday, 0 otherwise			23.17
Month	Survey month			
Jan (ref.)	1 if January, 0 otherwise			8.22
Mar	1 if March, 0 otherwise			6.51
Aug	1 if August, 0 otherwise			9.59
Daycare	Preference of having daycare center near home			
daycare_high (ref.)	High preference			20.66
daycare_low	Low preference			49.89
RetailCnt400	Number of retail opportunities in 400m from home	1.17	3.07	
FAR_Retail_Wk	Ratio of building footprint to retail parcel area in 500m from workplace	0.36	0.28	

Table 3.5: Descriptive statistics of selected worker variables for WOW tours

Variable	Description	Mean	SD	Percent
WOWComplexity	Average trip per work-other -work (WOW) tour	2.51	1.75	
PersonMode	Major mode used in all WOW tours of the day			
Auto (ref.)	1 if auto is the main mode of all tours, 0 otherwise			48.22
Walk	1 if all tours are taken by walking, 0 otherwise			44.93
WorkDuration_hr	Work duration in hour	6.92	2.00	
Month	Survey month			
Jan (ref.)	1 if January, 0 otherwise			6.85
Dec	1 if December, 0 otherwise			6.58
Male	1 if male, 0 if female			54.52
HHstructure	Structure of household			
UsualHH (ref.)	1 if the household has two of more adults and no child(ren) of age<16, 0 otherwise			
Couple_kid	1 if the household comprise a couple and child(ren) of age<16, 0 otherwise			36.16
ParkingWork	Monthly parking cost in dollars	19.42	44.57	
Park	Preference of having parks near home			
park_high (ref.)	High preference			75.62
park_low	Low preference			4.38
Entropy5_1000	Entropy in 1 km from home, computed with five land-use categories	0.52	0.14	
ServiceCnt_Wk	Number of service opportunities in 500m from workplace	24.20	28.64	

a sequence of importance – transit, auto, and then walk. If all HOH tours were taken by auto then the *PersonMode* is 'auto' for HOH tours. If, on the survey day, two or more different modes were used to take HOH tours, the *PersonMode* is categorized as 'other'.

3.3.3 Regression specifications

As mentioned above, the dependent variable representing tour complexity is the average number of trips per tour. We model worker and non-worker separately. For worker, there are three dependent variables – tour complexity of HOH tours, HW/WH tours, and WOW tours. Non-workers undertake only HOH tours, thus one dependent variable to be modeled. Since the data are continuous, we apply linear regression. However, for worker, the complexity of one type of tour is likely to influence another. For instance, if the workers make non-work stops during commute tours (HW/WH), they might not need to trip chain the home-based, non-work tours (HOH). Thus, it is logical to expect that the error terms of the three worker-models are correlated.

Based on this conjecture, we first applied the seemingly unrelated regression (SUR) technique to model three types of tour complexity. The SUR relaxes the assumption of independent error terms of ordinary least squares (OLS) and estimates the parameter through generalized least squares estimation (Zellner, 1962). However, the results (not reported here) suggest that the SUR is not appropriate for the given dependent variables. The reason is the presence of a large number of missing values in tour-specific variables (such as, mode choice, day or month) of HOH and WOW tours. Since very few workers took HOH (*N*=502) and WOW tours (*N*=365) compared to HW/WH tours (*N*=876), the missing values of tour-specific variables of HOH and WOW components dictate the model. When dummies for missing values are included in the model, the $R^2$of HOH and WOW components become greater than 0.99. Also, the Breusch-Pagan test statistic for error-correlation becomes insignificant. When the dummy variables for missing values are removed, the signs of almost all the coefficients change, indicating the spuriousness of the estimates. If we had travel data for a longer period, say one week, we would have more doers of HOH and WOW tours and a joint regression structure (SUR or structural equations modeling) would be applicable.

Therefore, we resort to OLS regression. There are four distinct models, three for worker and one for non-worker. Since the distribution of tour complexity for all four types of tour is highly skewed (Table 3.1), we transform them using the natural logarithm. The average number of *trips* per tour was proved to be a better metric of tour complexity than average *stops* per tour. Because the latter would contain many zeroes in the HW/WH tour, which would make the log-transformation impossible.

We explored the spatial autocorrelation of four dependent variables and found that the log-transformed values of the dependent variables are spatially correlated for non-worker tours (*Moran's I* = 0.0184, *p-value* = 0.005) and worker's HW/WH tour (*Moran's I* = 0.0164, *p-value* = 0.001). Also, the Lagrange Multiplier Test of OLS suggested that the error terms were correlated for the two models. In both cases, the test statistics suggested that a spatial lag model would perform better than a spatial error model. Although the

Moran's I for worker HOH and WOW were not significant, to keep things consistent we utilize spatial lag modeling for all four models. The models take the following formulations

$$Ln(Y_{TC(OLS)}) = \beta_0 + \beta_{Tour}X_{Tour} + \beta_{SE}X_{SE} + \beta_{ATT}X_{ATT} + \beta_{WE}X_{WE} + \beta_{BE}X_{BE} + \varepsilon \quad (4)$$

$$Ln(Y_{TC(LAG)}) = \beta_0 + \beta_{LAG}WY_{TC} + \beta_{Tour}X_{Tour} + \beta_{SE}X_{SE} + \beta_{ATT}X_{ATT} + \beta_{WE}X_{WE} + \beta_{BE}X_{BE} + \varepsilon \quad (5)$$

Here, Y_{TC} is the tour complexity (TC), that is, the average number of trips per tour; X_{Tour},X_{SE}, X_{ATT}, X_{WE}, and X_{BE} are respectively the sets of tour-specific and time-related variables, socio-demographics, attitude, weather, and built environment variables, and their corresponding notations of βs are the coefficients to be estimated. Equation (4) is the formulation of ordinary least square (OLS) regression while the equation (5) represents a spatial lag model. The spatial lag model tackles the spatial autocorrelation of errors (ε) by introducing a spatial lag variable, WY_{TC} where W is the standardized spatial weight N×N matrix (N=number of observations) with zero diagonal values, and β_{LAG} is the spatial lag parameter (Anselin, 1988). We used OpenGeoDa 0.9.8.14 to compute spatial weight matrix and for spatial lag modeling[14]. We used distance weight keeping the default minimum distance (approx. 6 km for worker and 7 km for non-worker) to allow at least one neighbor to every observation.

[14]GeoDa is opensource software, available at http://geodacenter.asu.edu/software/downloads.

3.4 Results

Tables 3.6 and 3.7 respectively report the results of worker and non-worker tour complexity. Although the complexity of workers' HOH and WOW tours are not susceptible to the spatial autocorrelation problem, the complexity of HW/WH tours and non-worker HOH tours are. For the sake of consistency we display the spatial lag estimates of all four models. However, the reader would notice that for worker HOH and WOW, the estimates and significance levels are the same in OLS and the spatial lag models. As to the HW/WH and non-worker HOH models, the spatial lag results are slightly different than OLS. In the following discussion, any reference to estimates will indicate the spatial lag estimates.

3.4.1 Worker tour complexity

As can be seen from Table 3.6, variables of all categories, except the weather variables, are significant at the 90% significance level. The mode choice has anticipated effects on tour complexity. A worker, who did all commute tours (HW/WH) by walking, made simpler tours compared to a worker who made all such tours by car. A similar effect is evident for HOH and WOW tours. Likewise, a worker made simpler HOH tours if using transit. A similar association of mode choice and tour complexity was observed in previous studies (Bhat, 1997; Chen et al., 2008). The reason is simple – transit is not convenient for trip chaining because of its fixed schedule and slower pace. We also tested the history dependency of tour participation, that is, whether or not the participation in a type of tour impacts the complexity of other tours. We observe such a tradeoff between HOH and HW/WH tours. If the workers did at least one HOH tour, they made simpler commute tours, compared to someone who did not make any HOH tour. No such tradeoff is found to be significant for other tour-types.

The impact of work duration on tour complexity is similar in magnitude and direction for HW/WH and WOW tours. A worker who spends too much time at the workplace makes a simpler commute, and midday non-work tours. The duration (Lee et al., 2009) and distance (Maat and Timmermans, 2006) of complex tours are higher than that of simple tours. Thus, longer work duration constrains a worker to undertake complex HW/WH and WOW tours.

We observe an interesting variation of tour complexity across weekdays and months. Workers make simpler HW/WH and HOH tours on Monday compared to Friday. This is probably because of more shopping and other maintenance activities on Friday to avert such tasks during the weekends. Workers make simpler commute tours at the beginning of spring (March) and fall (August) compared to winter (January). The plausible explanation for the workers to make more non-work trips during a commute tour in winter is to avoid more frequent going out of home (and workplace) in the cold. Also, it is interesting to see that complex WOW tours are taken in December. The possible explanation is – a majority of the workplaces are in the urban core where most shopping opportunities are located. In December, workers go out of the office to shopping centers

Table 3.6: Regression results for worker's three types of tours: home-work or work-home, home-other-home, work-other-work (values in the parentheses are the t-statistics). Dependent variable: Natural logarithm of average number of trip per tour

	HW / WH tour		HOH tour		WOW tour	
	OLS	Spatial lag	OLS	Spatial lag	OLS	Spatial lag
Weight		0.23 (1.86)		-0.35 (-1.46)		0.01 (0.04)
Constant	0.97 (16.18)	0.84 (9.15)	1.06 (16.2)	1.41 (5.61)	0.85 (10.00)	0.84 (4.83)
Time and tour related attributes						
PersonMode (ref: Auto)						
Transit			-0.17 (-1.72)	-0.17 (-1.75)		
Walk	-0.29 (-3.81)	-0.28 (-3.83)	-0.26 (-3.89)	-0.26 (-3.97)	-0.07 (-2.34)	-0.07 (-2.38)
HOH_Tour	-0.20 (-6.68)	-0.19 (-6.69)				
WorkDuration_hr	-0.04 (-7.09)	-0.03 (-7.13)			-0.03 (-3.74)	-0.03 (-3.79)
Monday (ref: Friday)	-0.08 (-2.41)	-0.08 (-2.43)	-0.07 (-1.68)	-0.07 (-1.69)		
Month (ref: January)						
Mar	-0.11 (-1.97)	-0.13 (-1.99)				
Aug	-0.10 (-2.07)	-0.11 (-2.12)				
Dec					0.22 (3.76)	0.22 (3.81)
Socio-demographics						
Male					0.08 (2.71)	0.08 (2.74)
BusPass	0.21 (3.71)	0.20 (3.80)				
Income (ref: above 100,000)						
Inc_below20	-0.13 (-2.47)	-0.15 (-2.46)				
Inc_20to40	-0.06 (-1.70)	-0.06 (-1.79)				
HHstructure (ref: UsualHH)						
Couple_kid	0.10 (3.09)	0.09 (3.03)			0.07 (2.11)	0.07 (2.14)
SingleParent	0.22 (2.62)	0.22 (2.58)				
HealthGood (ref: HealthPoor)			0.10 (2.60)	0.10 (2.61)		
ParkingWork					-0.00 (-1.86)	-0.00 (-1.89)

Table 3.6 Continued

Attitude						
daycare_low (ref: daycare_high)	-0.05 (-1.79)	-0.06 (-1.85)	-0.08 (-2.32)	-0.08 (-2.31)		
NearPostOffice (ref: PO_high)						
PO_low			0.13 (2.45)	0.13 (2.49)		
PO_med			0.15 (2.99)	0.15 (3.02)		
park_low (ref: park_high)					0.25 (3.39)	0.24 (3.44)
Built environment						
RetailCnt400	-0.02 (-2.96)	-0.01 (-2.90)				
entropy5_400			-0.27 (-2.71)	-0.28 (-2.82)		
entropy5_1000					0.22 (2.01)	0.22 (2.04)
FAR_Retail_Wk	0.15 (2.83)	0.17 (2.94)				
SWperArea_Wk			-0.00 (-1.98)	-0.00 (-2.05)		
ServiceCnt_Wk					0.00 (2.20)	0.00 (2.23)
Model summary						
Model with control variables						
R^2	0.161	0.165	0.079	0.080	0.171	0.171
Log likelihood		-461.071		-196.370		-51.76
Model with control and BE variables						
R^2	0.175	0.179	0.099	0.100	0.191	0.191
Log likelihood		-453.721		-190.452		-47.353
N	876		502		365	

for Christmas shopping. Thus, there is a monthly variation to tour complexity, but surprisingly there is no significant effect of weather variables.

A number of personal and household attributes play a role in worker tour complexity. Although there is no significant gender difference in the complexity of HW/WH and HOH tours, males make more complex WOW tours. Workers who own a bus pass make more complex commute tours. As we saw above, transit users make simpler HOH tours. Both findings indicate an interesting fact that workers, who use transit, are more inclined to trip chain during commuting tours than home-based, non-work tours. Further, from Table 3.1 it is noticeable that most workers make complex commute tours, while few of them make complex home-based and work-based, non-work tours. These findings indicate to higher tendency of workers to trip chain during commute tours compared to other tours.

Personal income has a profound, negative influence on HW/WH tour complexity. Workers of the two lowest income groups make simpler commute tours than workers of the highest income level. The income effect is the strongest for the workers of the lowest income category. Their commute tour complexity is 15% less than the wealthiest workers. Maat and Timmermans (2006) also notice a positive income effect on trip chaining behavior. The parking fee at the workplace has a negative, marginal effect on WOW tours. Also, self-reported health status is positively related to HOH tour complexity. Workers who ranked their health condition “good” made 10 percent more complex HOH tours than those who reported the health condition to be “poor”.

As expected, household structure has a strong influence on tour complexity. If workers live with only his/her partner and child(ren) (age <15), they make complex HW/WH and WOW tours. Also, single parents do more trip chaining during HW/WH tours. In fact, single parents take 22% more trips during a commute tour than the workers who come from households with two or more adults with no children. This is because the single parents and the workers living with a partner and children tend to optimize their travel by trip chaining as they need to spend more time at home for childcare.

Several attitudinal variables are found to be significant. Workers who do not prefer to live near daycare make simpler HW/WH and HOH tours. A low preference for daycare indicates the absence of children in household. In other words, workers, who have children in the family, prefer to reside near daycare and make complex commute and HOH tours. This is in line with our previous observation concerning the household structure variables. Workers, who have low and medium preference to live near a post office, make more complex HOH tours than workers who have a higher preference. This variable implicitly indicates the preference to live near services. A worker who likes to live farther from services makes more complex home-based, non-work tours. Similarly, a lower preference to reside near parks results in more complex WOW tours. Once again, this variable is a surrogate of the residential preference for recreational facilities. We also examined preferences for travel mode, specifically transit, but none were significant in the model.

Once a base model with significant control variables (socio-demographics, attitude, and tour-specific variables) was obtained, the BE variables were entered into the model. If any control variable lost its significance due to the inclusion of a BE variable, we removed that BE variable from the model. Thus, the BE variables presented in Table 3.6 have *true* effects on trip chaining. From the magnitude and direction of BE variables we observe the following:

The presence of a higher number of retail opportunities near home negatively affects commute tour complexity. Similarly, a higher degree of land-use mix near home results in simpler HOH tours but complex WOW tours. This is probably an indirect manifestation of the trade-off between HOH and WOW tour complexity.

The ratio of building to parcel area (proxy of parking scarcity) near the workplace is positively related to commute tour complexity. Usually, parking is in short supply where density or accessibility is higher, that is, in the urban core. Thus, workers working in the urban core make more complex commute tours. We see a similar relation between the count of service opportunities near work and WOW tour complexity. The density of sidewalks near workplace is negatively related to HOH tour complexity. Once again, this variable is a trait of a high density, pedestrian friendly area. Having a workplace in such places, results in simpler HOH tours. This again indicates the trade-off between the complexity of HOH tours with HW/WH and WOW tours.

As mentioned earlier, the three models (HW/WH, HOH, and WOW) are independent. But, the BE coefficients of the three models corroborate with each other. Workers residing near opportunities where different land-uses are intermingled make simpler commute and home-based, non-work tours. On the other hand, workers who work in dense, pedestrian friendly areas (e.g. near urban core) make simpler home-based, non-work tours, but more complex commute and work-based, non-work tours. The contrasting effects of the BE on tour complexity are what Cao et al. (2008) call “efficiency” and “inducement” effects. A worker whose neighbourhood accessibility is poor makes complex HOH tours to achieve travel efficiency. Another worker who works close to opportunities makes complex commute and WOW tours, which indicates an inducing effect of BE on tour complexity. Simply put, workers living in low accessibility areas make complex tours near workplaces with higher accessibility.Van Acker and Witlox(2010) also conclude from their results that workers might take more non-work stops near the workplace.

It is worth noticing that BE variables at home are significant at different scales, at 400 meters and 1 km which supports Guo and Bhat (2007) that different aspects of the BE could be important at different neighborhood scales.

The BE variables make reasonable contributions to the $R^2$of all three models. The inclusion of the spatial dependency variable (*Weight*) improves the explanatory power of HW/WH model. It means the BE variables were not sufficient to explain the total spatial variation of dependent variable. This is somewhat unexpected given the fact that we included a comprehensive set of BE variables in the model. As mentioned before, Moran’s *I* for HOH and WOW tour complexity are not significant. This is why, in both models, the spatial dependency variables (*Weight*) are not significant and the spatial lag models do not improve the R^2over OLS.

3.4.2 Non-worker tour complexity

As with the worker tour complexity, non-worker tour complexity is also influenced by travel mode. People who travel by transit or walk or a combination of auto, transit or walk, made simpler tours than auto-users. The daily variation of tour complexity follows a similar pattern to that of workers, that is, non-workers make simpler tours on Monday, compared to Friday.

Unlike the worker models, gender has a significant influence over non-worker tour complexity. Males make simpler home-based tours compared to their female counterparts, which is in per with the literature (Cao et al., 2008). This is because females shoulder most household responsibilities. Like workers, a non-worker single parent takes more complex tours than someone from a household with two or more adults with no kids. The number of workers and school-goers (age >15) have negative effects on non-worker tour complexity. This is because those members share some out-of-home household maintenance activities.

Only one attitude variable is significant – preference to walk after dark. This is in fact a proxy of several variables – attitude towards walking, neighborhood walking environment, etc. A person with moderate preference to walk makes 7% fewer trips in a tour than someone with a low walking preference.

Two built environment variables are significant in the model – shortest distance from home to regional malls and entropy at 1 km buffer. People living farther from regional malls make complex tours. Land-use mix has an opposite impact. Living in a

Table 3.7: Regression results for non-worker's home-other -home (HOH) tour complexity (values in the parentheses are the t-statistics). Dependent variable: Natural logarithm of average number of trip per tour

	OLS		Spatial lag	
	Coeff.	t-stat	Coeff.	t-stat
Weight			0.16	0.76
Constant	1.46	19.26	1.28	5.19
Time and tour related attributes				
PersonMode (ref: Auto)				
Transit	-0.12	-2.04	-0.12	-2.06
Walk	-0.43	-4.60	-0.43	-4.61
Other	-0.25	-4.92	-0.25	-5.00
Monday (ref: Friday)	-0.10	-2.94	-0.11	-3.02
Socio-demographics				
Male	-0.11	-3.53	-0.11	-3.59
SingleParent (ref: UsualHH)	0.26	1.85	0.26	1.89
HHworker	-0.05	-3.07	-0.06	-3.11
HHschoolgoer	-0.11	-2.87	-0.11	-2.93
Attitude				
SafeWalk_med (ref: SafeWalk_low)	-0.06	-2.05	-0.07	-2.12
Built environment				
RegMalls_Hm	0.02	1.86	0.01	1.83
entropy4_1000	-0.24	-1.85	-0.24	-1.85
Model summary				
Model with control variables				
R^2	0.125		0.135	
Log likelihood			-259.935	
Model with control and BE variables				
R^2	0.147		0.147	
Log likelihood			-254.555	
N	638			

mixed land-use area, results in making simpler home-based tours. We saw a similar effect of land-use mix on worker HOH tour complexity. It is worth mentioning that entropy was also significant at the 400m buffer, but the value of the coefficient is considerably higher at the 1 km scale. In the case of the worker model, entropy was significant only at 400m. Also, we experimented with the number of land-uses when computing entropy. In the worker model, the variable *entropy5_400* (Table 3.6), was calculated using five land-use categories– residential, commercial, office, institutional, and parks. Since the computation is based on area, we suspected that the inclusion of parks would bias the metric. So we computed a second entropy metric, without park. The variable in the non-worker model, *entropy4_1000* (Table 3.7), is computed with only four land-uses, excluding park. The other entropy measure was not significant at 400m or 1 km.

Unlike workers' HW/WH model, the BE variables in this model suffice to tackle the spatial autocorrelation problem. As displayed in Table 3.7, the spatial dependency variable (*Weight*) is not significant in the spatial lag model and so it does not improve the model R^2over OLS. Comparing the worker and non-worker models we come to the conclusion that non-workers' home-based tour complexity is easier to explain by BE than the complexity of workers' commute tours.

3.5 Conclusion

The objective of this chapter was to examine how the BE affects trip chaining behavior. The motivation stems from an increasing practice of trip chaining and the popularity of Smart Growth as a TDM instrument. Our analyses provide some interesting findings on this matter. First, BE does have separate impacts on a person's daily tour complexity after residential self-selection is controlled for. Higher accessibility and land-use mix deter from taking complex home-based, non-work tours. Put another way, a non-worker living away from opportunities make complex tours to *efficiently* conduct out-of-home, non-work activities. Second, a worker living in a highly accessible, mixed-use neighborhood makes simpler non-work tours, but working in such areas lead to a complex commute and work-based, non-work tours. The picture we get here is that people living in suburban areas, away from opportunities; try to overcome the poor accessibility by scheduling their out-of-home activities to more complex tours. Since most workers work in high accessibility areas, they chain their commute and work-based trips, thereby offsetting any constraints they might face by living in poor accessibility neighborhoods.

Also, our model-results as well as findings from other studies suggest that auto-users do more trip chaining. Thus, implementation of any policy to increase public transit usage would have a lesser impact on those who are used to trip chaining. It is also noticeable from Table 3.1 that most workers trip chain during commuting whereas few workers undertake complex home-based or work-based tours. Thus, trip chaining contributes to peak-hour traffic congestion to some extent.

Overall, from a transportation planning perspective, trip chaining is not a welcoming aspect of travel behavior. Our findings provide both caution and encouragement to the advocates of Smart Growth. Planners and growth managers should be cautious when predicting the travel outcomes of compact, mixed-use developments. As long as housing supply is available in low-density neighborhoods, people predispositioned towards bigger lots with backyards, who like auto travel and compensate poor accessibility through trip chaining, would want to reside there. The good news is, once people start to dwell in compact neighborhoods with diverse land-uses, their neighborhood characteristics are likely to influence their trip chaining behavior. The results from our cross-sectional data suggest this. But, it can be verified once longitudinal data are available.

There are, however, a few limitations of this study. The trip chaining data used in the analyses are just a one-day snapshot of weekday travel. Travel diaries of one or two weeks would provide more reliable representations than cross-sectional data. Such datasets would contain more doers of home-based and work-based, non-work tours and different types of tours could be modeled within a joint modeling framework, such as SUR. Although we used a comprehensive set of BE variables, the spatial autocorrelation problem remained in the OLS of commute tour complexity indicating the need for some other BE variables. Future studies on commuting trip chaining might consider the BE along the home-work route. With the use of GPS technology in activity-based surveys, it would be easy to identify the usual commute route. Until then, the shortest path from home to work could be assumed as the usual commute route.

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4 Conclusions

The purpose of this study was to examine the influence of built environment on travel behavior in Halifax Regional Municipality. Two aspects of travel was analyzed – non-work travel distance by auto and complexity of trip chains. As to the auto travel distance, it was hypothesized that people living and working in high accessibility area make shorter trips. Chapter 2 tests this hypothesis. A selection of non-work trips was used in the analysis. Work trips were excluded because they largely depend on factors other than built environment, such as, labor market, residential location choice, real estate market, etc (Crane and Crepeau, 1998). Two types of non-work trips were also excluded. They are – travel for in-home socializing (e.g. visiting friend's place) and transportation assistance (pick-up or drop-off). How far one would travel for in-home socializing depends on one's social network (Carrasco and Miller, 2006); it is not likely to be influenced by the built environment. The pick-up or drop-off trips were excluded because the trip purpose of the person who was picked-up or dropped off was not known; it could be a work trip which was excluded from the study. Overall, the analysis included the aggregate distance by auto of around 47 percent and 73 percent of all trips made by worker and non-worker respectively. The total auto distance in a weekday was regressed against built environment near home and workplace while socio-demographics, attitudinal and weather variables were accounted for. The results suggest that built environment has a fairly strong influence on daily auto distance when the self-selection effect was controlled for. The built environment variables improved the R^2 of worker and non-worker model by 7.3 percent and 5.2 percent respectively. The worker auto distance is influenced by the built environment near both home and workplace. Residential self-selection does have some influence over auto travel distance, but the impact of built environment is much stronger. The results go in favor of the first hypothesis, that people living and working in compact, mixed-use and high accessibility areas travel shorter distance by auto for non-work trips.

The second aspect of travel that was modeled is tour complexity (Chapter 3). In this study a tour or trip chain was defined based on two anchors – home and workplace. If a journey is started from home (or workplace) and ended to home (or workplace), it is called a tour. If several stops are made during a tour, it is called a complex tour. The metric used in this study for tour complexity is the average number of trips per tour in a weekday. All trips were included in the analysis. Since workers have two anchors, home and workplace, they make three types of tours – home-based, non-work tours; home to work or work to home tours, and midday work-based, non-work tours. Non-workers make only home-based, non-work tours. Four linear regression models and four spatial lag models were developed for different types of worker and non-worker tours. The results suggest that a worker, whose residence is poorly accessible and workplace is highly accessible, make complex commute and work-based, non-work tours. This suggests that workers compensate poor neighborhood accessibility by trip chaining near workplace. The non-workers make complex home-based tours if they live in low-density, single use neighborhoods. It is also evident from the models that worker and non-worker, who trip chain, are auto dependent. The impact of built environment on trip chaining is in line with the second hypothesis that people compensate poor accessibility by chaining their trips. This provides both caution as well as encouragement to the planners who are trying to reduce auto dependency by smart growth development.

If there is a supply of households in low-density, single-use neighborhoods and people living there try to compensate the poor residential accessibility by trip chaining, smart growth and other TDM instruments will have lesser impact on their travel behavior. However, if the planners direct urban growth towards more compact and mixed-use development, in the housing market there will be more supply of accessible households than poorly accessible ones. Once people start to live in those neighborhoods, they are likely to make simpler tours and depend less on auto. The study is based on cross-sectional data. Once longitudinal data are available, this finding can be thoroughly verified.

By definition, trip chaining should result in efficient utilization of road space as less return trips are made when trips are chained together. This is beyond the scope of second hypothesis. However, one can compare the results of auto distance models (Chapter 2) and tour complexity models (Chapter 3) as similar sample is used in both analyses. The former has a smaller sample size than the latter, because a selection of non-work trips was included in the analysis of auto travel distance while all trips were considered in tour complexity models. Still, same respondents (and survey days) along with some additional respondents were included in tour complexity analysis which makes the results of both analyses comparable. Tour complexity models indicate that living in poorly accessible areas results in higher complexity of tours. The auto distance models reveal that poor accessibility results in farther auto travel. One can easily deduce from the findings that although people, who live in poor accessibility area, trip chains more, their overall travel distance by auto is still higher than those living in highly accessible neighborhoods. Future attempts on trip chaining and travel distance in a unified modeling structure would be able to unravel more indirect relations among built environment and these aspects of travel behavior (trip chaining and travel distance).

It is worth noting that the explanatory powers of tour complexity models are less than those of auto distance models. This suggests that trip chaining is more difficult to explain than auto travel distance. In addition, the contribution of built environment variables in the R^2 of tour complexity models is much lower than that of auto distance models. This is probably because the latter set of models included only a selection of non-work trips while the former models included trips of all purpose. As explained earlier, work trips, trips for in-home socializing and trips for transportation assistance are not really associated with built environment.

The study makes several contributions to the literature. First, it analyzes two different aspects of travel – auto distance and trip chaining. Second, a comprehensive set of built environment variables, including the 3Ds and several accessibility measures, are used in modeling. They are computed at different geographical scales, and near home and workplace. Third, spatial lag models are used along with linear regression and the performance of built environment variables are assessed. Fourth, the study examines the influence of weather conditions on travel behavior. This is particularly important for

Canada because of its extreme weather, particularly during the winter. Surprisingly, very few studies (e.g. Fan and Khattak, 2008) examine the effects of weather on travel. Fifth, although extensive works have been done on travel – built environment relation in the US as well as in many countries of Europe, very few (Mitra et al., 2010; Potoglou and Kanaroglou, 2008) is done in Canadian context. The study also makes significant policy contribution. The current growth policy for HRM – Halifax Regional Municipal Planning Strategy – envisages promoting public transit and discouraging auto travel through smart growth initiatives. The results of this study support such growth policy.

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