



# Role of the built environment on trip-chaining behavior: an investigation of workers and non-workers in Halifax, Nova Scotia

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## Abstract

This study examines the influence of the built environment on trip-chaining behavior. Based on weekday travel in the Halifax Regional Municipality, we develop four separate models of tour complexity, each corresponding to a specific type of tour. The average number of trips per tour is regressed against built environment characteristics while household, personal, and tour-specific characteristics and residential self-selection are controlled. We apply ordinary least squares regression and spatial lag models and use a comprehensive set of density, diversity, design, and accessibility metrics near home and workplace. The results indicate that higher accessibility and mixed land-use is associated with simpler home-based, non-work tours. Workers residing away from opportunities make complex tours near workplaces located in high accessibility areas. Auto users make more complex tours. Also, most workers make complex commute tours compared to home-based or work-based non-work tours. In general, individuals compensate for the poor accessibility of residential locations by making complex tours, relying on auto, and chaining non-work trips with commuting. The significant role of attitudinal variables is also observed, thus revealing the presence of residential self-selection in trip-chaining behavior.

**Keywords** Built environment · Spatial lag model · Tour · Travel behavior · Trip chaining

## Abbreviations

TB	Travel behavior
BE	Built environment
TDM	Travel demand management
HRM	Halifax Regional Municipality
STAR	Space-Time Activity Research
CBD	Central business district
HOH	Home-other-home

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HW/WH	Home-work or work-home
WOW	Work-other-work
OLS	Ordinary least squares

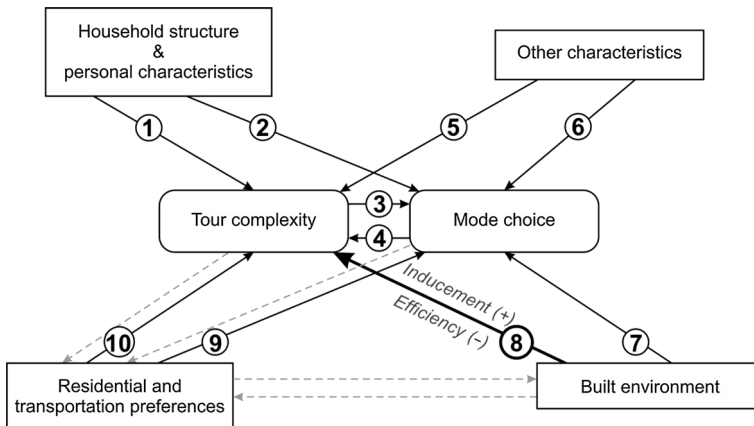
## Introduction

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 face, especially in urban areas (Recker et al. 2001). Trip chaining is a common phenomenon in urban areas for many reasons, including the growing need to spend more time at work, the growth of multi-worker households, and the increased affordability and taste for particular commodities (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 1 is a simple schematic representation of the factors hypothesized to influence trip chaining. How many stops (or trips) are made in a tour (or trip chain) is a measure of tour complexity. 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 worker may drop off children to daycare en route to work (link 1 in Fig. 1) and for that, the automobile 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 particular goods. 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 suburban neighborhood 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 Fig. 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 a desirable travel behavior from a transportation planning perspective. However, findings from a number of studies suggest the opposite. First, when a commute trip is chained with non-work stops, it deteriorates peak-hour traffic congestion (Ye et al. 2007). Second, trip chaining results in more challenges to TDM measures aimed at promoting 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; Wang 2015).

So far, our understanding on the relation between the BE and trip chaining is unclear. We cannot say for certain 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.



**Fig. 1** Factors affecting trip-chaining complexity

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 Fig. 1) while accounting for all other links (except link 3).

The next section outlines briefly the literature, especially factors observed to influence 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 the conclusion.

## 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).

Most trip-chaining studies have examined the effect of household and personal characteristics (link 1 in Fig. 1) on trip-chaining behavior. For instance, in multi-worker households, female workers tend to chain non-work trips to their commute 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 greater responsibilities of single parents compared to other adults. Similar effects are observed by Noland and Thomas (2007): 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 greater shopping ability and/or a higher degree of activity participation (Maat and Timmermans 2006).

Many studies focus on understanding the mode choice of chained trips (links 3 and 4 in Fig. 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 making simple tours to use 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 reliance on transit decreases. Modeling auto ownership and propensity to use auto in a tour, Chen et al. (2008) draw a similar conclusion: As the number of stops in a tour increases, the propensity to use auto increases. A recent study in Sydney, Australia reveals that the spatial distribution of destinations of a tour influences the choice of mode of the tour. If various activities, such as shopping, social activities, personal business, etc. can be performed within walking distance, public transit is the likely mode for a complex tour. However, if multi-purpose stops are spatially dispersed, they are combined in a car tour (Ho and Mulley 2013).

Interesting work is undertaken by Ye et al. (2007) regarding the relation between mode choice and trip chaining. They explore three hypotheses: the 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 to be the most significant. However, in all three models, the results indicate that if individuals are forced to take a complex tour, they are likely to choose car for the tour. The positive association between auto-usage and trip chaining can be explained by the higher degree of flexibility offered by cars 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 between trip chaining and 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 areas with poor accessibility make complex tours in order to use their out-of-home time efficiently. 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. For instance, if they forget to buy something, they can just go out and purchase the product since shops are close by. This leads to another hypothesis: People living in high-accessibility neighborhoods make more frequent tours. Crane (1996) and Krizek (2003b) confirm the second hypothesis: High density increases tour complexity. Noland and Thomas (2007) corroborate the first hypothesis by finding that density has a negative effect on tour complexity. Cao et al. (2008) refer to the effect described by the first hypothesis as the “efficiency” effect since the residents of suburbs tend to efficiently use 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 preferring to live closer to opportunities make more stops. Also, people preferring to minimize travel

make more stops (“efficiency” effect). However, most studies do not report the inducement effect. For example, in a study of household tour complexity, Krizek (2003a) finds that households living in areas characterized by high accessibility make simple but more frequent tours. Wallace et al. (2000) also observe a similar phenomenon 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) concerning trip chaining and the BE 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.

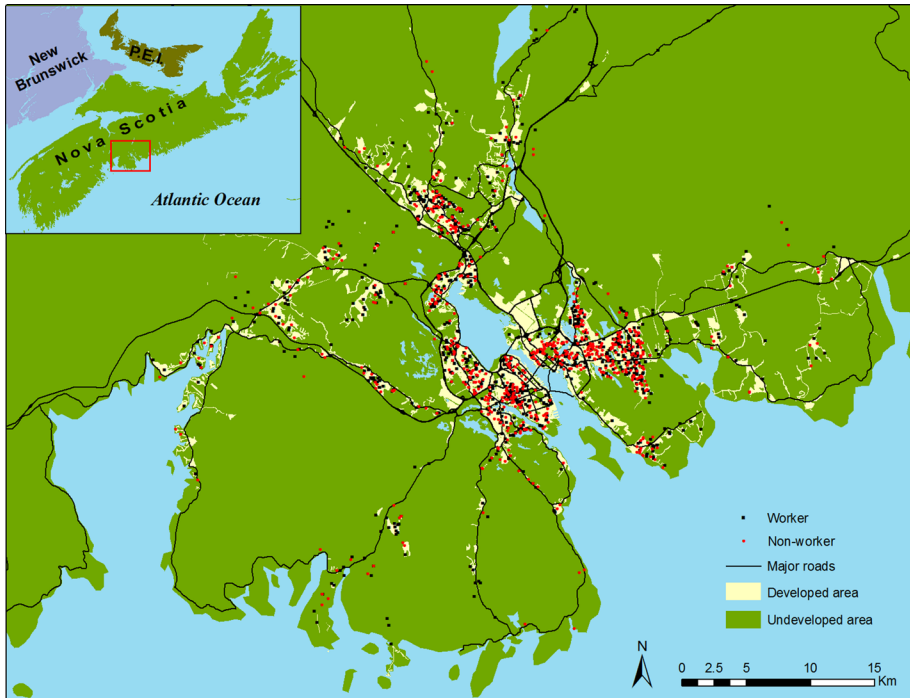
More recently, similar efforts have been made to explain several travel aspects along with trip chaining. Applying several independent regressions, Maat and Timmermans (2006) examine the influence of the BE on activity participation, tour complexity, and travel distance. Their study provides some interesting findings. First, density is positively related to tour complexity (average number of trips per tour), which seems to support the induced trip chaining described by Cao et al. (2008). This is contrasted by the results of a second model (percent of complex tours) which suggest that people living in the suburbs are more likely to make complex tours (this 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. Their nested logit model reveals 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. Looking at the impact of neighborhood characteristics on the complexity of various tours, Lee (2015) observes that people living in a walking, transit-friendly area in the City of Los Angeles, take less chained non-work tours. However, such effects are limited for work-tours. On the other hand, a study in Beijing, China suggests that higher density at residential neighborhoods leads to simpler, more frequent tours while high-density, mixed use environments around workplaces are associated with more complex work-based tours (Ma et al. 2014).

Although attempts have been made to understand the impact of the BE on trip chaining, very few studies account for the residential self-selection effect, 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 such as 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.

## Data and methods

### Data sources

The study area, the Halifax Regional Municipality (HRM), is a county located in Nova Scotia, Canada (Fig. 2). The tour data for this study are obtained from the Space-Time Activity Research (STAR) project, which collected data between April 2007 and May



**Fig. 2** Part of Halifax Regional Municipality displaying all respondents' (workers and non-workers) home locations

2008. The time-use diary of the STAR data set contains 2-day activity information for 1971 respondents age 15 years and older who were selected from 1971 randomly chosen households. The diary contains the time, location (fixed locations and travel modes), and several other attributes for each activity performed by the respondents over 48 h. The location of each activity was recorded through a global positioning system (GPS) device that respondents carried throughout the survey period.

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) data set; a 2008 DMTI road network dataset; a 2006 building footprint and a 2006 sidewalk data set obtained from the HRM Department of Planning and Development Services; and 2006 Census of Canada data. In addition, meteorological information for each day of the survey period was collected from Environment Canada's website.<sup>1</sup>

<sup>1</sup> [http://www.climate.weatheroffice.gc.ca/climateData/hourlydata\\_e.html?Prov=NS&StationID=6358&Year=2007&Month=4&Day=1&timeframe=1](http://www.climate.weatheroffice.gc.ca/climateData/hourlydata_e.html?Prov=NS&StationID=6358&Year=2007&Month=4&Day=1&timeframe=1).

## Variables

### Tour complexity

In this study, we defined a tour or a trip chain based on two anchors: home and workplace. When a journey begins 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 min there. The 90 min 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 largest amount of time every day. Other places in their activity space are where they go occasionally to fulfill certain needs (shopping, leisure, socializing, etc.).

Based on two anchors, we identified three types of tours: home to other places then back home (HOH); home to work<sup>2</sup> 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.

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, 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 than on weekends due to greater time constraints and more roadway congestion. We focused the analysis on 1-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 2 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, and tour mode choice, amongst others. 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, which corresponds to 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 1 shows the average complexity of different types of tours.

### Built environment variables

We computed a comprehensive set of BE variables used in the trip-chaining literature. Also, we measured BE characteristics at two different scales: 400 m and 1000 m

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<sup>2</sup> Work refers to both work and school.

**Table 1** Average weekday tour complexity of workers and non-workers

Average trips per tour	Non-worker HOH	Worker		
		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

The values shown correspond to the number of respondents

straight-line buffers around the home and 500 m buffers around the workplace. The 400 m buffer is used commonly in the literature (Boarnet and Sarmiento 1998; Krizek and Waddell 2002). The 1000 m scale was derived from the distribution of home-based, walking-trip distance where more than 80% of trips were within 1000 m from home. This indicates that 1 km defines the walk-shed in HRM. We found the workplace walk-shed to be ½ km.

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 the 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 sidewalk to road length. In addition, the ratio of building footprint to parcel area near workplace was computed as a proxy measure of parking space availability (Frank et al. 2010). The mathematical formulation for the entropy index is

$$Entropy = \frac{\sum_{i=1}^k (p_i)(\ln p_i)}{(\ln k)} \quad (1)$$

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

$$HHI = \sum_{i=1}^k (p_i \times 100)^2. \quad (2)$$

The notations are the same as for the entropy index.

The second category of BE variables comprise three types of accessibility (Scott and Horner 2008). They are: gravity, proximity, and cumulative opportunity for five types of



opportunities: retail, service, religious, leisure, and active recreation. For any category, the gravity accessibility is

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

Here  $A_i$  is the gravity accessibility;  $W$  is the weight of opportunity,  $j$ ;  $\beta^3$  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. Cumulative opportunity 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 (Cervero and Kockelman 1997; Bagley and Mokhtarian 2002). However, we chose to use original variables because they are easy to interpret and intuitive to policy makers. To minimize issues concerning multicollinearity, we first explored correlations among the BE variables through a correlation matrix. Among highly correlated variables, only one was chosen for our models.

### 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; sex; 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 young children, couples with older children, single person, and single parent); number of workers and number of school-goers in the household; and monthly cost of parking at work (if worker). Tables 2, 3, 4 and 5 display some descriptive statistics of selected variables.<sup>4</sup>

We control for residential self-selection by including attitude variables in the models. The variables represent preferences towards residential location and travel mode. The STAR questionnaire had more than 30 attitudinal questions. From Wilcoxon Signed Rank tests we observed that some of the attitudinal variables were not significantly different from others. We selected those variables that were representative of others and deemed to have important policy implications. Most variables were dichotomous and the rest were 3-point scale responses. Sixteen attitude variables remained after the Wilcoxon Signed Rank tests: 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; convenience, cheapness, safety, and accessibility of transit; and workaholic or not. Controlling for attitudes towards travel and residential choices in statistical models is one way of handling residential self-selection

<sup>3</sup> The value of  $\beta$  was determined empirically. We ran a regression model with distance of every trip destination from home as the independent variable and the natural logarithm of trip frequency as the dependent variable. The model coefficient gave the value of  $\beta$ .

<sup>4</sup> Due to space limitations we only display the variables that are significant in our models. The descriptive statistics of other variables are available upon request.

**Table 2** Descriptive statistics of selected non-worker variables for HOH tours

Variable	Description	Mean	SD	Percent
HOHComplexity	Average # of trips per home-other-home (HOH) tour	3.59	1.68	
PersonMode	Major mode used in all HOH tours of the day			82.13
Auto(ref.)	1 if auto is the main mode of all tours, 0 otherwise			6.27
Transit	1 if transit is the main mode of all tours, 0 otherwise			2.51
Walk	1 if all tours are taken by walking, 0 otherwise			9.09
Multiple	1 if the tours are taken by different modes, 0 otherwise			
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	Household structure			
Couple_Kid16+(ref.)	1 if the household consists of a couple and child(ren) of age $\geq 16$ , 0 otherwise			27.49
SingleParent	1 if the respondent is a single parent, 0 otherwise			1.10
HHWorkers	Number of workers in the household	0.74	0.87	73.98
HHSchoolgoers	Number of school-goers (age $\geq 16$ ) in the household	0.14	0.41	14.42
SafeWalk	Feeling safe to walk after dark			
SafeWalk_Low (ref.)	1 if respondent does not feel very safe, 0 otherwise			11.60
SafeWalk_Med	1 if respondent feels moderately safe, 0 otherwise			50.94
RegMalls_km	Shortest distance from home to regional malls (km)	6.50	6.37	
Entropy4_1000m	Entropy within 1 km from home, computed with four land-use categories	0.44	0.14	

**Table 3** Descriptive statistics of selected worker variables for HOH tours

Variable	Description	Mean	SD	Percent
HOHComplexity	Average # of trips per home-other-home (HOH) tour	2.95	1.51	
PersonMode	Major mode used in all HOH tours of the day			88.25
Auto (ref.)	1 if auto is the main mode of all tours, 0 otherwise			2.79
Transit	1 if transit is the main mode of all tours, 0 otherwise			6.37
Walk	1 if all tours are taken by walking, 0 otherwise			
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			
Health_Poor (ref.)	1 if respondent's health is poor, 0 otherwise			1.00
Health_Good	1 if respondent's health is good, 0 otherwise			21.31
Daycare	Preference of having daycare near home			
Daycare_High (ref.)	1 if high preference, 0 otherwise			22.71
Daycare_Low	1 if low preference, 0 otherwise			47.81
PostOffice	Preference of having post office near home			
PO_High (ref.)	1 if high preference, 0 otherwise			12.35
PO_Low	1 if low preference, 0 otherwise			34.06
PO_Med	1 if moderate preference, 0 otherwise			53.19
Entropy5_400m	Entropy within 400 m from home, computed with five land-use categories	0.39	0.17	
SidewalkDensity_wk	Sidewalk length (km) per square km within 500 m from workplace	9.04	9.58	

**Table 4** Descriptive statistics of selected worker variables for HW/WH tours

Variable	Description	Mean	SD	Percent
HWComplexity	Average # of trips 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
HOHTour	1 if any HOH tour is taken during the survey day, 0 otherwise			57.31
WorkDuration_hr	Work duration in hours	7.02	2.37	
BusPass	1 if the respondent has a bus pass, 0 otherwise			7.20
HHStructure	Household structure			
Couple_Kid16+(ref.)	1 if the household consists of a couple and child(ren) of age $\geq 16$ , 0 otherwise			27.28
Couple_Kid15	1 if the household consists of 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_100+(ref.)	1 if income $\geq \$100,000$ , 0 otherwise			9.47
Inc_Below20	1 if income $< \$20,000$ , 0 otherwise			8.90
Inc_20 to 40	1 if $\$20,000 \leq \text{income} < \$40,000$ , 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			
January (ref.)	1 if January, 0 otherwise			8.22
March	1 if March, 0 otherwise			6.51
August	1 if August, 0 otherwise			9.59
Daycare	Preference of having daycare center near home			
Daycare_High (ref.)	1 if daycare preference is high, 0 otherwise			20.66
Daycare_Low	1 if daycare preference is low, 0 otherwise			49.89

**Table 4** (continued)

Variable	Description	Mean	SD	Percent
RetailOpp_400m	Number of retail opportunities within 400 m from home	1.17	3.07	
FAR_Retail_Wk	Ratio of building footprint to retail parcel area within 500 m from workplace	0.36	0.28	

**Table 5** Descriptive statistics of selected worker variables for WOW tours

Variable	Description	Mean	SD	Percent
WOWComplexity	Average # of trips 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 hours	6.92	2.00	
Month	Survey month			
January (ref.)	1 if January, 0 otherwise			6.85
December	1 if December, 0 otherwise			6.58
Male	1 if male, 0 if female			54.52
HHSstructure	Structure of household			
Couple_Kid16+(ref.)	1 if the household consists of a couple and child(ren) of age $\geq 16$ , 0 otherwise			28.49
Couple_Kid15	1 if the household consists of a couple and child(ren) of age $< 16$ , 0 otherwise			36.16
ParkingCosL_wk	Monthly parking cost at work in dollars	19.42	44.57	
Park	Preference of having parks near home			
Park_High (ref.)	1 if park preference is high, 0 otherwise			75.62
Park_Low	1 if park preference is low, 0 otherwise			4.38
Entropy5_1000 m	Entropy within 1 km from home, computed with five land-use categories	0.52	0.14	
ServiceOpp_wk	Number of service opportunities within 500 m from workplace	24.20	28.64	

(Mokhtarian and Cao 2008). However, it should be pointed out that the attitudinal questions in the STAR dataset do not capture the full extent of respondents' preferences towards certain types of residential areas and important attributes such as preferences for larger homes over accessibility are not present in the data. Thus, residential self-selection may not be fully accounted for in the models. Nonetheless, the variables include preference towards neighborhood accessibility to workplace and various facilities, and attitudes regarding transit and walking, thus representing self-selection to some extent.

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 in tour complexity. January was the reference month and we anticipated more complex tours during spring and summer months compared to winter. Tour-specific variables consist of the modes a person chose to take for all tours of a specific type. For example, if a worker did all HW/WH tours by auto, the worker's *PersonMode* is auto for HW/WH tours. We assigned the main mode of a tour according to a sequence of importance: transit, auto, and walk. If, on the survey day, two or more different modes were used to take tours of a particular type, the *PersonMode* was categorized as 'multiple'.

## 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 dependent variables are continuous, we apply linear regression. However, for worker, the complexity of one type of tour is likely to influence another. For instance, if workers make non-work stops during commute tours (HW/WH), they might not need to take 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 simultaneously the complexity of the three tour types. The SUR relaxes the assumption of independent error terms of ordinary least squares (OLS) and estimates the parameters 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 for tour-specific variables (such as mode choice, day, and month) corresponding to HOH and WOW tours. Since fewer workers took HOH ( $n=502$ ) and WOW tours ( $n=365$ ) compared to HW/WH tours ( $n=876$ ), the missing values for the tour-specific variables of HOH and WOW dictate the model. When dummies for missing values are included in the model, the  $R^2$  values of HOH and WOW 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 1 week, we would have more

representation of HOH and WOW tours and a joint regression structure (SUR or structural equations modeling) would have been applicable.

Therefore, we adopt OLS regression. There are four distinct models, three for worker and one for non-worker. Since the distributions of tour complexity for all four types of tours are highly skewed (Table 1), we transform them using the natural logarithm. The average number of trips per tour was shown 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 the four dependent variables and found that the log-transformed values of the dependent variables were spatially correlated for non-worker tours (*Moran's I* = 0.0184, *p value* = 0.005) and worker HW/WH tours (*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 utilized spatial lag modeling for all four models. The models take the following formulations

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

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

where  $Y_{TC}$  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 (Liu et al. 2016), and built environment variables, and the corresponding  $\beta$ s are coefficients to be estimated. Equation (4) is the formulation of ordinary least squares (OLS) regression while Eq. (5) represents a spatial lag model. The spatial lag model tackles the spatial autocorrelation of errors ( $\varepsilon$ ) by introducing a spatial lag variable,  $WY_{TC}$  where  $W$  is the standardized spatial weight  $N \times N$  matrix ( $N$  = number of observations) with zero diagonal values, and  $\beta_{LAG}$  is the spatial lag parameter (Anselin 1988). We used OpenGeoDa<sup>5</sup> 0.9.8.14 to compute the spatial weight matrix and to perform the spatial lag modeling. We used distance weight keeping the default minimum distance (approx. 6 km for workers and 7 km for non-workers) to allow at least one neighbor for every observation. Maximum likelihood is used to estimate the spatial lag models.

## Results

Tables 6 and 7 report respectively 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 will notice that for worker HOH and WOW, the OLS and spatial lag estimates are identical. As for the HW/WH and non-worker HOH models, the OLS and

<sup>5</sup> OpenGeoDa is open source software, available at <https://geodacenter.asu.edu/software>.



**Table 6** Regression results for workers' three types of tours: home-work/work-home, home-other-home, and work-other-work (values in parentheses are the *t*-statistics)

	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						
Walk	-0.29 (-3.81)	-0.28 (-3.83)	-0.17 (-1.72)	-0.17 (-1.75)	-0.07 (-2.34)	-0.07 (-2.38)
HOHTour	-0.20 (-6.68)	-0.19 (-6.69)	-0.26 (-3.89)	-0.26 (-3.97)		
WorkDuration_hr	-0.04 (-7.09)	-0.03 (-7.13)				
Monday (ref: Friday)	-0.08 (-2.41)	-0.08 (-2.43)	-0.07 (-1.68)	-0.07 (-1.69)	-0.03 (-3.74)	-0.03 (-3.79)
Month (ref: January)						
March	-0.11 (-1.97)	-0.13 (-1.99)				
August	-0.10 (-2.07)	-0.11 (-2.12)				
December					0.22 (3.76)	0.22 (3.81)
Socio-demographics						
Male						
BusPass	0.21 (3.71)	0.20(3.80)			0.08 (2.71)	0.08 (2.74)
Income (ref: Above_100)						
Inc_Below20	-0.13 (-2.47)	-0.15 (-2.46)				
Inc_20 to 40	-0.06 (-1.70)	-0.06 (-1.79)				
HHSStructure (ref: Couple_Kid16+)						
Couple_Kid15	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)				

Table 6 (continued)

	HW/WH Tour		HOH Tour		WOW Tour	
	OLS	Spatial Lag	OLS	Spatial Lag	OLS	Spatial Lag
Health_Good (ref: Health_Poor)			0.10 (2.60)	0.10 (2.61)		
ParkingCost_wk×100					-0.06 (-1.86)	-0.06 (-1.89)
Attitude						
Daycare_Low (ref: Daycare_High)	-0.05 (-1.79)	-0.06 (-1.85)	-0.08 (-2.32)	-0.08 (-2.31)		
PostOffice (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						
RetailOpp_400m	-0.02 (-2.96)	-0.01 (-2.90)				
Entropy5_400m			-0.27 (-2.71)	-0.28 (-2.82)		
Entropy5_1000m					0.22 (2.01)	0.22 (2.04)
FAR_Retail_Wk	0.15 (2.83)	0.17 (2.94)				
SidewalkDensity_wk×10			-0.03 (-1.98)	-0.04 (-2.05)		
ServiceOpp_wk×10					0.01(2.20)	0.01(2.23)
Model summary						
Model with control variables						
R <sup>2</sup>	0.161	0.165	0.079	0.080	0.171	0.171
Model with control and BE variables						
R <sup>2</sup>	0.175	0.179	0.099	0.100	0.191	0.191
n	876		502		365	

Dependent variable is the natural logarithm of average number of trips per tour

**Table 7** Regression results for non-workers' home-other-home tour complexity. Dependent variable is the natural logarithm of average number of trips per tour

	OLS		Spatial Lag	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
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: Couple_Kid16+)	0.26	1.85	0.26	1.89
HHworkers	-0.05	-3.07	-0.06	-3.11
HHschoolgoers	-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_km	0.02	1.86	0.01	1.83
Entropy4_1000m	-0.24	-1.85	-0.24	-1.85
Model summary				
Model with control variables				
R <sup>2</sup>	0.125	0.135		
Model with control and BE variables				
R <sup>2</sup>	0.147	0.147		
n	638			

spatial lag estimates differ. In the following discussion, references to estimates correspond to the spatial lag models.

### Worker tour complexity

As can be seen from Table 6, variables of all categories, except the weather variables, are significant at the 90% significance level. The mode choice has expected 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 between 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 whether or not participation in one type of tour impacts the complexity of other tours. We observe such a tradeoff between HOH and HW/WH tours. If workers undertook at least one HOH tour,

they made simpler commute tours, compared to workers who did not make any HOH tours. No such tradeoff is found to be significant for the other tour types.

The impact of work duration on tour complexity is similar in magnitude and direction for HW/WH and WOW tours. As time spent at work increases, tour complexity decreases. Previous research has found that the duration (Lee et al. 2009) and distance (Maat and Timmermans 2006) of complex tours are greater than those for simple tours. In turn, given a finite time budget, increasing work duration constrains a worker to undertake simpler 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 on the weekends. Workers make simpler commute tours at the beginning of spring (March) and fall (August) compared to winter (January). A plausible explanation for making more non-work trips during a commute tour in winter is to avoid leaving home more frequently when it is cold outside. Also, it is interesting to see that more complex WOW tours are taken in December. A possible explanation is that a majority of the workplaces are in the urban core where shopping opportunities are located. In December, workers may leave the office for Christmas shopping. Interestingly, despite the monthly variation in tour complexity, weather variables are insignificant.

A number of personal and household attributes play a role in worker tour complexity. Although the complexity of HW/WH and HOH tours does not vary by sex, men make more complex WOW tours than women. Workers who own a bus pass make more complex commute tours. As we saw above, transit users make simpler HOH tours. Together these findings suggest that workers who use transit are more inclined to trip chain during commute tours than for home-based, non-work tours. Further, from Table 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 a higher tendency for workers to trip chain during commute tours compared to other tours.

Personal income influences HW/WH tour complexity. Workers of the two lowest income groups undertake simpler commute tours compared to workers of the highest income group. The income effect is strongest for the workers of the lowest income category. Their commute tour complexity is 15% less than that of the highest income earners. Maat and Timmermans (2006) also notice a positive income effect on trip chaining behavior. The parking cost at the workplace has a negative, marginal effect on WOW tours. Also, self-reported health status is positively related to HOH tour complexity. Specifically, HOH tour complexity was 10% greater for workers ranking their health as ‘good’ than for those ranking their health as ‘poor’.

As expected, household structure has a strong influence on tour complexity. Workers living with partners/spouses and young children (age < 16 years) make more complex HW/WH and WOW tours. Also, single parents do more trip chaining during HW/WH tours. In fact, single parents’ commute tours are 22% more complex than those of workers living with partners/spouses and older children (age ≥ 16 years). A likely explanation for these findings is that single parents and workers living with partners/spouses and young children tend to have greater household responsibilities and must therefore compensate for related time commitments by optimizing out-of-home maintenance activities by chaining such activities to their commutes.

Several attitudinal variables are found to be significant. Workers who are indifferent to living near daycare facilities make simpler HW/WH and HOH tours. A low preference for daycare suggests an absence of very young children in household. In other words, workers

who have very young children 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 preferences to live near a post office make more complex HOH tours than workers who have a high preference. Preference to live near a post office is an indicator of the preference to live near services. A worker who prefers 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. This variable is a surrogate for the preference for recreational facilities near home. We also examined preference for transit, but it was insignificant.

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 the BE variable from the model. Thus, the BE variables presented in Table 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 retail building area to retail parcel area (proxy of parking scarcity) near the workplace is positively related to commute tours. 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 number of service opportunities near work and WOW tour complexity. The density of sidewalks near the workplace is negatively related to HOH tours. Once again, this variable is a trait of a high density, pedestrian friendly area. 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. However, the BE coefficients of the three models corroborate with each other. Workers residing 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 (near the 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 (2011) 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 m and 1000 m 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 the HW/WH model. It means the BE variables were not sufficient to explain the total spatial variation of the 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 is insignificant. This is why, in both models, the spatial dependency variables (*Weight*) are not significant and the spatial lag models do not improve the  $R^2$  over OLS.

### Non-worker tour complexity

As with 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, sex has a significant influence over non-worker tour complexity. Males make simpler home-based tours compared to their female counterparts, which is in line with the literature (Cao et al. 2008). This is likely because females continue to shoulder more household responsibilities. Like workers, a non-worker single parent takes more complex tours than someone from a household consisting of a couple and older children. The number of workers and the number of school-goers (age > 15) have negative effects on non-worker tour complexity. This is because those members may 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. Tours for a person with a moderate preference to walk after dark are 7% less complex than those for someone with a low walking preference.

Two built environment variables are significant in the model: shortest distance from home to regional malls and entropy for a 1000 m buffer around home. Tour complexity increases with distance from regional malls. Land-use mix has the opposite effect. As entropy increases, tour complexity decreases suggesting that living in a mixed land-use area results in simpler home-based tours. We found a similar effect of land-use mix on worker HOH tour complexity. It is worth mentioning that entropy was also significant for the 400 m buffer, but the value of the coefficient is considerably higher at the 1000 m scale. In the case of the worker model, entropy was significant only at 400 m. Also, we experimented with the number of land-uses when computing entropy. In the worker model, *Entropy5\_400m* (Table 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 in the non-worker model would bias the metric. Consequently, we computed another entropy metric that did not contain parks. The variable in the non-worker model, *Entropy4\_1000m* (Table 7), is computed with only four land-uses, excluding parks. The other entropy measure was insignificant at both 400 m and 1000 m.

Unlike the worker HW/WH model, the BE variables in the non-worker model are sufficient to tackle the spatial autocorrelation problem. As displayed in Table 7, the spatial dependency variable (*Weight*) is not significant in the spatial lag model and so it does not improve the model  $R^2$  over 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 the BE than the complexity of workers' commute tours.

## Conclusion

The objective of this study was to examine how the BE affects trip-chaining behavior. The motivation stems from the 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 controlling for residential self-selection. 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 makes complex tours to pursue out-of-home, non-work activities efficiently. Second, a worker living in a highly accessible, mixed-use neighborhood makes simpler non-work tours, but working in such areas leads to complex commute and work-based, non-work tours. The picture we obtain here is that people living in suburban areas, away from opportunities, try to overcome 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 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.

From a transportation planning perspective, trip chaining is not a welcome aspect of travel behavior. Our findings provide both caution and encouragement to 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 reside 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 can be verified once longitudinal data are available.

Our study contributes to the literature concerning the relationship between trip chaining and the BE in three meaningful ways. First, several factors associated with this complex relationship are discussed based on findings in the literature (Fig. 1). While past studies examined some of the factors and their impacts on trip chaining, the models presented in this study control for all of the factors. Second, our analysis incorporates a comprehensive suite of BE variables derived for both residential neighborhoods and workplaces. These variables measure density, diversity, design, and accessibility. Further, they are measured at different scales and the results confirm that some BE variables have better explanatory power if measured at one scale compared to others. Third, residential self-selection is accounted for in the models through attitudinal variables. Thus, the effects of the BE on trip chaining observed here are more robust compared to those reported in other studies.

There are, however, a few limitations of this study. The trip-chaining data used in the analyses are for a 1-day snapshot of weekday travel. Travel diaries of 1 or 2 weeks would provide more reliable representations than cross-sectional data. Such data sets 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 other BE variables. Future studies on commute 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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