Exploring the relationship between urban form and nonwork travel through time use analysis

Ming Zhang

Sutton Hall 3.124A, 1 University Station Stop B7500, School of Architecture, The University of Texas, Austin, TX 78712, USA

Available online 18 December 2004

Abstract

This paper presents an activity-based time-use analysis of the relationship between urban form and nonwork travel. Using data from the 1991 Activity–Travel Survey in Boston, the study tested the role of spatial accessibility as a composite measure of urban form in explaining individuals’ nonwork activity participation, travel times, and travel frequencies. The results showed varying effects of modifying spatial accessibility on nonwork activity participation and travel among different activity categories. When accessibility to schools improved, children and adults were found to pay more visits to and spent more times in schools yet without generating additional total school travel. However, for every standard deviation increase in accessibility to entertaining, recreational, eat-out, and other social opportunities, the odds were 1.23 times greater to engage in these activities than staying at home. In contrast, the odds were 0.79 for them to spend time in chauffeuring family members. There was a substitution relationship between work commute and nonwork travel when levels of accessibility changed. An increase in accessibility by 1 standard deviation was associated with a decrease in work commute by 2.23 min, but increases in travel times for social activities by 2.07 min and for shopping travel by 1.20 min. The increase in social travel was due to more frequent trip making resulting from higher accessibility. Findings from the study underscore the importance of physical planning and design to improve spatial accessibility and to help divert the additional social travel induced by accessibility improvement to nondriving modes.

© 2004 Elsevier B.V. All rights reserved.

Keywords: Activity-based travel analysis; Time use; Urban form; Nonwork travel; Boston

1. Introduction

Travel demand has persistently increased over the past three decades. A particularly noteworthy trend is the increasing share of travel for shopping, personal business, recreational, social, and other nonwork purposes. National travel surveys show that in 1969 nonwork accounted for approximately 75% of person-trips (PT) and nearly 65% of vehicle miles traveled (VMT). By 2001, the shares of nonwork travel had increased to over 85% of PT and 72% of VMT (McGuckin and Srinivasan, 2003; U.S. Department of Transportation, 2003). The growing travel demand is adding an enormous burden onto the limited transportation infrastructure. Travel-associated side
effects – congestion, pollution, and greenhouse gas emissions – are also imposing tremendous pressures on the natural and the built environment.

To better understand the growth of travel and to identify policy options that help manage travel demand, researchers are adopting a new paradigm for travel analysis, namely the activity-based travel analysis (Kitamura, 1988; Bhat and Koppelman, 1999). Building on the premise that travel demand is derived from the demand for participation in activities (Mitchell and Rapkin, 1954), the new approach focuses on individual decisions regarding when and where to participate in what activities and for how long. A central element of the new approach is the conceptualization of time, where time is treated as both costs and resources to individuals (Pas and Harvey, 1997). Any activity–travel requires consumption of time and everyone has a time-budget of 24 h a day. Individuals allocate time from their daily time budget among various activities and associated travel to meet personal and household needs. Analyzing the time allocation decisions allows us to gain insights into individuals’ decisions to participate in activities and their demand for travel.

In addition to time, the new approach also brings a spatial dimension of activity participation into travel demand analysis. This is because participating in activities requires access to activity destinations in certain locations. In the physical environment of cities and regions, travel attractions (e.g., jobs, stores, restaurants, etc.) are separated spatially and connected to each other via transportation networks, some clustering together while others are spread out. The way they are distributed and connected provides a spatial context, i.e., the urban form, in which individuals travel to reach their desirable destinations. Like the time factor, urban form also presents both constraints and opportunities to individuals’ activity participation and travel.

Research on individuals’ time-use has accumulated a large body of literature (see Bhat and Koppelman, 1999). Publications on the link between urban form and trip making are also voluminous (see Badoe and Miller, 2000; Crane, 1999; Ewing and Cervero, 2001). Yet there have been relatively limited studies that apply a time-use framework to investigate the relationship between urban form and travel, especially the travel for nonwork purposes. The study presented in this article attempted to fill the gap. Its main goal is to expand the knowledge base on the linkage between urban form and travel that not only is valuable to travel demand analysis but also has important implications to the practice of environmental design, urban planning, and land development. Evidence obtained from the analyses will provides empirical and behavioral foundations to recent planning and design efforts, commonly known as the New Urbanism, including neo-traditional neighborhood design, transit-oriented development, and more broadly, Smart Growth, which have set driving reduction as part of their objectives (Calhoun, 1993; Cervero, 1989; Duany et al., 1991; Katz, 1993; Newman and Kenworthy, 1999; Urban Land Institute, 2000).

This study focused on one specific aspect of urban form—spatial accessibility. Denoted to the ease to reach employment and service opportunities, accessibility is one of the most important concepts in defining and explaining urban form and function. Through accessibility there exists a systematic relationship between the spatial distribution of activity destinations and the amount of travel within a region. Public policy-making related to the public and private transportation investments and the locations of economic and service activities has continuously modified the spatial accessibility of regions. Because of the importance of accessibility, meeting accessibility goals for all components of the population has long been vocally recommended as a key objective of transportation and social policies (Cervero, 1996; Handy, 1994; Shen, 1998, 2000; Wachs and Kumagai, 1973). In essence, the main planning and design goal of the New Urbanism and Smart Growth initiatives is to create an urban form (in various spatial scales) that provides enhanced access to choices for housing, employment, retail and recreational services, and other opportunities but with less demand for vehicle travel.

Nevertheless, the anticipated transportation benefits of the New Urbanism and Smart Growth initiatives have been a topic of heated debate. This is evident by the growing literature in the area. One source of debate relates to the net travel outcome associated with accessibility improvement. Conceptually, accessibility improvement leads to shorter travel times (or distances) on a per trip basis and higher quantity, better quality of destination opportunities. On the other hand, under the economic assumption of rational behavior, reduced travel time or distance and increased
attraction of destination opportunities likely induce additional consumption of the services and generate more frequent travel (Crane, 1996). This is particularly likely with the nonwork, discretionary travel. As a result, the net travel effect of improving accessibility becomes ambiguous and should be determined empirically. Literature in the area so far has reported mixed findings (see review in the next section).

This study was partly motivated by providing additional empirical evidence to help clarify the ambiguity of the travel effects of improving accessibility. For this purpose, three aspects of activity–travel as they relate to accessibility need to be analyzed: activity participation, travel duration, and activity–travel frequency. Specifically, the study addressed the following two questions:

(1) How does spatial accessibility relate to individuals’ decisions to participate in nonwork activities such as shopping, social, personal business, and others? Answering this question provides a behavioral foundation to examine the potential changes in travel as a result of accessibility changes. It was hypothesized that higher accessibility to the services at activity destinations contributed to a stronger tendency to participate in these activities. Higher accessibility leaded to more attractive services or lower costs to access the services. Therefore, individuals were willing to consume more of the services and spend more time in them.

(2) How does accessibility relate to nonwork travel in terms of travel duration and activity–travel frequency? Total travel in a given period of time, e.g., a day, is a combination of travel duration (in terms of time or distance) of individual trips and travel frequency in the same time period. As discussed earlier, accessibility affects the two aspects of travel in the opposite directions. The magnitudes of the effects tend to vary, depending on travel purposes, travelers’ socio-economic characteristics, and the spatial and temporal context in which the travel takes place.

This article presents the study in five parts. After Section 1, Section 2 reviews previous studies. Section 3 presents analytical framework and methodology. Section 4 reports the results of the empirical analysis of the Boston case. Finally, Section 5 concludes the analysis.

### 2. Previous studies

There are extensive reviews of studies on individuals’ time use decisions and the link between the urban form and trip making (see Badoe and Miller, 2000; Bhat and Koppelmon, 1999; Crane, 1999; Ewing and Cervero, 2001). This review will highlight nonwork activities and travel as they relate to the physical environment of cities and regions. Compared with work and work-related commute, nonwork activities and travel have been relatively less studied, partly because work commute exhibits strong peaking effects due to the spatial and temporal regularities of work trips. These peaking effects often cause traffic congestion and therefore garner much attention from the general public and policy makers. In contrast, nonwork activities and travel are relatively spread out across the geography and throughout the day. Furthermore, there are many different kinds of nonwork activities. The irregularity in characteristics and diversity in types make study of nonwork activities and associated travel a particularly challenging task.

A strong tradition of travel demand modelers’ work is the development of statistical models to predict individuals’ activity participation and travel. Studies by Bhat et al. (1999), Bhat and Gossen (2003), and Ma and Goulias (1998) are among those who incorporated the urban form variables in their models. Bhat et al. (1999) studied shopping activities by modeling shoppers’ stop making and trip chaining behavior in the Boston area. In that study, the authors applied a gravity-model-based accessibility measure to characterize the spatial distribution of shopping destinations. Their empirical results indicated the strong effects of accessibility to shopping opportunities, along with other variables, on both stop generation and organization. They observed that the influence of accessibility on shopping trips was important when the existing level of accessibility was low, for example, for households residing in rural areas. In another study, Bhat and Gossen (2003) focused on weekend recreational activity. They estimated a mixed multinomial logit model of weekend recreational activity participation using the 2000 San Francisco Bay Area Travel Survey. From the modeling results they found that two urban form variables, zonal employment density and land use mix, predicted recreational activity with marginal significance.
Other studies were explanatory in nature, testing the statistical power of urban form variables in explaining nonwork activity and travel. Handy (1994, 1996) studied shopping travel behavior by relating it to the spatial structure of regional and neighborhood environment. She proposed measures of shopping accessibility at different spatial scales, namely regional and local accessibility. While both measures took the gravity-model form, local accessibility considered shopping destinations such as retail, services, and others within a traffic analysis zone. In contrast, regional accessibility measures access to regional retail centers. Her study of the sample data from the San Francisco Bay Area showed that higher levels of both local and regional accessibility were associated with shorter average shopping distances but were not associated with higher shopping frequency. As a result, higher levels of both local and regional accessibility were associated with less total shopping travel. Furthermore, the effect of high levels of local accessibility was greatest when regional accessibility was low and vice versa. This finding was similar to that of Bhat and Gossen (2003) on recreational activities. In a further study of shopping behavior in Austin, TX, Handy and Clifton (2001) recommended land use strategies to encourage local shopping. According to them, such strategies may not necessarily reduce total shopping travel but do help increase quality of life.

Kraak (2003) adopted the same measures as Handy’s (1994) and characterized urban form at different spatial scales, including regional accessibility to retail service opportunities and local accessibility to neighborhood stores. In addition, an index variable was developed to summarize neighborhood built environment in terms of density, land use mix, and street patterns. His study was unique in that he looked at people’s tour making behavior instead of individual trips of specific purposes. A tour is a sequence of trips that begin and end at home. Examining travel tours allowed him to account for the interconnections among trips for different purposes. This is a more accurate representation of travel behavior in the real world than the traditional, trip-based analytical approach. His empirical analysis of the Puget Sound region (Seattle, WA) showed that households living in areas with higher levels of neighborhood access made more tours and fewer stops per tour. They made more frequent tours for work and maintenance (personal, appointment, shopping) purposes. Regional accessibility, however, was found having insignificant influence to tour making.

Rajamani et al. (2003) studied both shopping and recreational travel in the Portland, OR, area by incorporating a set of urban form variables at the regional as well as the neighborhood scale. Focusing on travel mode choice behavior, their results of the multinomial logit modeling indicated that residents in areas with higher regional accessibility had a greater preference for recreational trips. Furthermore, an increase in residential density decreased the probability of driving alone and mixed-uses promoted walking behavior for nonwork activities. Greenwald and Boarnet (2001) focused on nonwork pedestrian travel. Their findings in general confirmed the importance of the physical environmental variables to this particular travel mode. In another study, Greenwald (2003) tested the New Urbanist ideas about travel mode substitution through alternative physical planning and design for nonwork trips. He found that New Urbanist design practices did promote walking substitution for vehicle trips.

Nevertheless, not all the existing studies have found significant evidence to affirm a relationship between urban form and nonwork travel. Crane and Crepeau (1998) studied travel mode choice for nonwork trips without distinguishing among different types of nonwork activities. Using the travel diary survey for San Diego, CA, they estimated a set of probit regression models to test the link between street network patterns and mode split while controlling for trip distance and speed. From the analysis, they found no evidence that street network patterns mattered for decisions to drive vs. walk. Two other studies by Boarnet and Sarmiento (1998) and Boarnet and Crane (2001) used travel diary data from southern California residents to examine the link between characteristics of the built environment at the neighborhood level and nonwork trip generation. In these studies, the authors modeled the number of nonwork automobile trips as a function of sociodemographic variables and the physical environmental characteristics near the person’s place of residence. They found that the urban form variables were statistically insignificant in all but one of the model specifications.

Matt and Arentze (2003) examined whether activity participation and travel for work, school, and shopping purposes were influenced by urban form in the Netherlands. They quantified the characteristics of urban form
by spatial accessibility that was measured in terms of distances to shops and services and cumulative opportunities within certain threshold distances. Their analyses showed that patterns of activity participation were largely explained by the socio-demographic variables. Yet they found little evidence that activity patterns varied across spatial characteristics. The study by Levinson (1999) was among a few that systematically examined nonwork activities through time use analysis. He considered population density as a proxy of accessibility to activity centers. Because more activity opportunities are typically available in places with higher density, it was expected that a higher rate of outside home activity would be observed in denser areas. Nevertheless, his study of the 1990 Nationwide Personal Travel Survey showed mixed results on the effect of density on activity duration for shopping, travel, and other activity purposes.

There are recent efforts to develop conceptual and empirical frameworks for combined representation of spatial and temporal constraints in which individuals make activity and travel decisions. These efforts have been largely built on the notion of space–time prism introduced by Hagerstrand (Pred, 1981). For example, based on the space–time prism concept, Miller (1991, 1999) developed a network-based accessibility model and applied it to transportation analysis in a GIS environment. Kwan (1998, 1999) also studied individual accessibility developed from the space–time prism concept. Her focus was primarily on the visualization of the space–time prism, with particular attention to gender differences. Pendyala et al. (2002) incorporated both the time and the space dimension in activity–travel analysis. Using data sets from San Francisco and Miami areas, they developed and tested a methodology for estimating the temporal vertices of time–space prisms for each individual as a function of his or her socio-economic and demographic characteristics.

In summary, despite the large share of travel for nonwork purposes in total travel, there have been relatively less studies on nonwork activities and travel. Most existing studies focused on one or a few types of nonwork activities, for example, shopping and recreational activities. Some treated all nonwork activities as a single activity type. As a result, interactions and competitions among different nonwork purposes were omitted in the consideration of individuals’ time use decisions and activity participation. Furthermore, activities and travel for personal business, escorting, and social purposes have largely been neglected, although these activities and associated travel take much greater shares in daily time use than other nonwork travel. On the relationship between the urban form and nonwork activity–travel, existing studies have also reported mixed, inconclusive results. This paper attempts to fill the gaps in the literature by studying multiple nonwork activities and associated travel in an integrated framework of time-use analysis.

3. Analytical framework and methodology

3.1. Activity classification

To study time use/activity participation, the first task is to group numerous kinds of activities into a limited number of types in order to be analytically feasible and convenient. Reichmann (1976) suggests grouping activities into three types: (1) subsistence activities, including work or work-related business activities that are essential to provide financial support to the family; (2) maintenance activities, including family or personal business activities to satisfy the household and personal physiological and biological needs as well as cultural needs; (3) leisure activities, including social, recreational, and other discretionary pursuits motivated by cultural and psychological needs. Some of the activities are performed at home, whereas others take place outside the home in various locations.

This study followed Reichmann’s activity classification scheme with some modifications. All activities taking place inside home were grouped into one category, at home, because the main interest of this study was outside home nonwork activities, and because no detailed information on inside-home activities was available from the data sources. For outside home activities, work-related activities were differentiated from all nonwork activities. Outside home nonwork activities further were broken down into six specific types (Fig. 1):

- school: curricula, extra-curricula, and other school-based activities;
- shopping: all shopping activities;
- social: entertaining, recreational, eating out, etc.;
- personal: business, doctor visits, banking, etc.;
Fig. 1. Classification of an individual’s daily activities and time use.

- pick up/drop off: chauffeuring family members or friends for work, school, day care, or other places;
- other: civic, religious, and other activities.

For all activities taking place outside the home, an additional type of activity, travel, is necessary. Therefore, each of the above outside the home activities includes two components: activity and travel associated with the activity. Each of the activities consumes a certain amount of time: $T_1, T_2, \ldots, T_m$, and each time segment takes a share of the 24-h daily time budget:

$P_1 = \frac{T_1}{24}$, $P_2 = \frac{T_2}{24}$, \ldots, $P_m = \frac{T_m}{24}$ and

$$\sum_{i=1}^{m} P_i = 1$$

(1)

For some individuals, one or more activity types may have zero time shares because they do not necessarily participate in all types of activities in a given day. But the sum of the time share of all activities the individual participated in a day should be 24 h or 1440 min. Data observed from Activity–Travel Surveys were snapshots of individuals’ time allocation decisions in the survey period in the study area. The question under investigation is whether the revealed time use decisions suggest time use patterns that can be explained by individuals’ personal and household characteristics as well as social and environmental factors.

3.2. Theoretical underpinning and analytical model of time use/activity participation

Economic theory of resource allocation provides a conceptual framework to study individuals’ time use decisions (Becker, 1965; Gronau, 1977). Theory suggests that an individual gains utility from spending time in a specific activity, for example, earning income from work, meeting household needs from
shopping, attaining education from schooling, improving personal health from exercising, and achieving self-satisfaction from engaging in recreation, entertainment, and other social activities. For different individuals, however, the level of utility associated with time use in a specific activity varies, depending on individual characteristics (e.g., age, gender, and employment status), household needs (e.g., household size), availability of other resources (e.g., income and vehicle ownership), and constraints to activity participation imposed by society (e.g., work schedule, location, and distribution of activity destinations). When deciding which activity to participate in and for how long, an individual trades off time used for different activities based on his/her needs and preference. He/she allocates limited time resources to a combination of daily activities such that the total utility derived from participating in these activities is maximized.

From the above theory, time allocation becomes a choice decision determining how a given unit of time will be spent. Yet the individual’s underlying choice decision is unknown to the analyst. To analyze the choice decision process using the observed decision outcome, the analyst can express it in probability terms and model the probability of a time unit being spent in a specific activity as a function of a set of explanatory variables. Approximating the probabilities with observed time shares of all nonwork activities from the sample, one can then formulate the following set of logit regression models, subject to the condition expressed in Eq. (1) (Pindyck and Rubinfeld, 1998).

\[
\ln \left( \frac{P_m}{P_1} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \\
\ln \left( \frac{P_m}{P_2} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \\
\cdots \\
\ln \left( \frac{P_m}{P_3} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots 
\]

(2)

where \( P(m) \) is the probability of choosing or allocating a basic time unit to activity \( m \) out a set of activities \( m \) and \( X \) is a vector of explanatory variables. Vector \( \beta \) includes parameters to be estimated to capture the direction, significance, and magnitude of corresponding \( X \) in influencing decisions on time-use and activity participation.

In Eq. (2), \( P_1 \), or time-share of staying home serves as the base. It is assumed that every individual will eventually return home at the end of a day. At any time point, he/she can decide to go home or to continue the current activity. The estimated coefficients therefore reflect the effect of changes in \( X \) on the logarithm of the odds ratio (i.e., \( \ln(P_m/P_1) \)) of participating in outside home activity \( i \) versus staying home.

To account for the potential error correlation across the equations, Zellner’s seemingly unrelated regression estimation (SURE) was utilized to estimate the models in Eq. (2). The SURE model applies a generalized least squares method to ensure efficient estimates of coefficients (Green, 1997).

3.3. Characterizing the urban form

As discussed earlier, the physical setting of urban form presents both opportunities and constraints to individuals’ activity participation. To characterize these dual roles of urban form, this study adopted a gravity model-based measure of spatial accessibility, which takes the following general form known as the Hansen Accessibility model (Hansen, 1959):

\[ A_i = \sum_j O_j f(C_{ij}) \]

where \( A_i \), accessibility of zone \( i \), \( O_j \), measure of opportunities presented at destination zone \( j \), \( C_{ij} \), travel cost from zone \( i \) to zone \( j \); and \( f() \), impedance function, which may take various mathematical forms.

The particular appealing feature of this composite measure of urban form is that it captures multiple aspects of spatial interactions between people and opportunities presented throughout the geographic space. First, for destinations with more attractive opportunities, people are more likely to go to and thus spend more time there. This is measured by \( O_j \) in the model. Second, identical opportunities at destinations in farther locations are less attractive than those located nearby. This is reflected in the inclusion of an impedance function \( f() \) in the model. Third, people’s sensitivities to increases in travel distance or time vary depending on travel purposes and their personal and household characteristics. Variation in the magnitude of the parameters in the impedance function indicates such variation in sensitivity to spatial separation.

Accessibility modeling, whether using the original form as described above or with extensions to it,
produces a set of scores, one for each unit of analysis (e.g., TAZ). Mapping out the scores creates an accessibility surface for the study area, illustrating the spatial structure of the area and the relative location (dis)advantages of the people among the zones in the area. Over time, the accessibility surface transforms when changes take place in land use activities, transportation investments, or public policies that modify the spatial characteristics of the physical environment.

In addition to physical distance and geographic location, transportation constraints, for example, the availability of private vehicles and transit services, also affects people’s access to spatial opportunities significantly. This study looked at individuals’ activity participation in a 24-h period, in which the individual did not always use the same transportation means for all trips in the survey day. To consider variations in accessibility associated with different travel modes, this study extended the basic Hansen accessibility model and measured total accessibility at the zonal level (Shen, 1998).

Specifically, the total accessibility of a zone is the sum of accessibility by car and by transit. Spatially, the summation can be interpreted as an overlay of the accessibility potential surfaces of all travel modes. In equation form, the accessibility to a specific type of opportunity is given below:

\[ A^m_i = \sum_j O^m_j f(C^m_{ij}) + \sum_j O^m_j f(C^m_{ij}^{Transit}) \]  

(3)

where \( m \), types of activities, in this study \( m = 1, 2, \ldots, 8 \); \( A^m_i \), accessibility of zone \( i \) for activity type \( m \); \( O^m_j \), measure of opportunities presented at activity destination \( j \) for activity type \( m \); and \( C_{ij} \), travel cost from zone \( i \) to \( j \).

### 3.4 Data

The main data set used for this study was the 1991 Boston Activity–Travel Survey conducted by the Central Transportation Planning Staff (CTPS) in the Boston region. It is over 10 years old and may not be representative of current Bostonians’ travel behavior. Yet it was the most recent Activity–Travel Survey available at the time of this study. A number of studies have been published using the same data set (Ben-Akiva and Bowman, 1998, 2000; Bhat et al., 1999; Shen, 1998, 2000; Srinivasan and Ferreira, 2002; Zhang, 2004).

The survey population recorded in a diary the outside home activities over a 24-h period for each person over the age of five. Main variables recorded in the diary included starting time, ending time, purpose of each activity, and transportation means involved for the activity. Each person’s activity diary began in the morning when the person left home and ended in the evening when she/he arrived home. Data on the socioeconomic, demographic, and neighborhood characteristics of the households were also collected. There were 3854 households surveyed with a total of 9281 persons and 39,373 activity and travel records.

Not all of these records were usable for this study though. There were records that showed time-inconsistency, for example, having a total of more or less than 24 h of activities on the survey day. Missing data on individual socio-economic characteristics of the activity participants also made some records unusable. Furthermore, this study focused on persons age 16 and over. After all these factors were considered, the final data set contained 5173 persons for this study.

Table 1 reports descriptive statistics of the sample. For accessibility modeling, travel impedance data are also necessary. CTPS provided matrices of the 24-h average zonal travel times by car and by public transportation. Destination attractiveness measured by the number of employees in each zone serves as proxies of establishments that attract trip making. A trip length distribution table also was available for five different trip purposes, i.e., work, school, shopping, social, and nonhome-based other trips. Based on this table, an exponential function, shown below, was calibrated for each purpose to obtain parameters needed for the impedance calculations in the accessibility modeling.

\[ f^m(C_{ij}) = e^{\gamma^m C_{ij}} \]

where \( \gamma^m \) is a parameter for activity type \( m \).

Specifically, the parameters calibrated from the trip length distribution for various trip purposes are, respectively, work: \(-0.103\); school: \(-0.109\); shopping: \(-0.089\); other: \(-0.117\); and nonhome-based trips: \(-0.96\).

Employment data at the TAZ level are available in the following types: agriculture, industrial, retail, service, government, and total. For this study, three sets of accessibility scores were calculated: accessibility to retail, service, and total nonagriculture employment opportunities. In the time use analysis, accessibility to
Table 1
Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socio-economic/demographic/spatial</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (female = 1)</td>
<td>0.53</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age (years)</td>
<td>41.77</td>
<td>15.14</td>
<td>17</td>
<td>84</td>
</tr>
<tr>
<td>Licensed driver</td>
<td>0.93</td>
<td>0.26</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Employed (full time)</td>
<td>0.28</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Employed (part time)</td>
<td>0.38</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of persons in household</td>
<td>2.93</td>
<td>1.16</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Number of children aged five or less</td>
<td>0.22</td>
<td>0.54</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Number of persons employed</td>
<td>1.71</td>
<td>1.01</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Number of vehicles in household</td>
<td>1.62</td>
<td>0.72</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Household income (1991, US$ 1000’s)</td>
<td>55.12</td>
<td>29.38</td>
<td>15</td>
<td>120</td>
</tr>
<tr>
<td>Accessibility to all establishments</td>
<td>3.04</td>
<td>1.69</td>
<td>0.29</td>
<td>13.98</td>
</tr>
<tr>
<td>Accessibility to retail establishments</td>
<td>6.79</td>
<td>4.51</td>
<td>0.57</td>
<td>19.74</td>
</tr>
<tr>
<td><strong>Time use (activity + travel in minutes)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time at home</td>
<td>926.47</td>
<td>220.90</td>
<td>250</td>
<td>1435</td>
</tr>
<tr>
<td>Time at work</td>
<td>336.06</td>
<td>259.79</td>
<td>0</td>
<td>1125</td>
</tr>
<tr>
<td>Time at school</td>
<td>34.84</td>
<td>114.20</td>
<td>0</td>
<td>900</td>
</tr>
<tr>
<td>Time in shopping</td>
<td>30.49</td>
<td>54.67</td>
<td>0</td>
<td>775</td>
</tr>
<tr>
<td>Time in social</td>
<td>72.09</td>
<td>110.53</td>
<td>0</td>
<td>1050</td>
</tr>
<tr>
<td>Time in personal business</td>
<td>28.80</td>
<td>63.12</td>
<td>0</td>
<td>925</td>
</tr>
<tr>
<td>Time in pick up/drop off</td>
<td>10.46</td>
<td>33.40</td>
<td>0</td>
<td>735</td>
</tr>
<tr>
<td>Time in other activities</td>
<td>0.80</td>
<td>11.31</td>
<td>0</td>
<td>400</td>
</tr>
<tr>
<td>Time in total travel</td>
<td>84.85</td>
<td>80.95</td>
<td>0</td>
<td>770</td>
</tr>
</tbody>
</table>

4. Results of empirical analysis

The empirical analysis of the Boston case consists of two parts. Part one estimated a set of multinomial logit models of activity participation in which activity durations and travel times were combined for each type of nonwork activity. The purpose was to examine the effect of accessibility on nonwork activity participation while the effects of other personal and household variables were controlled for. Part two separated activity duration from travel and analyzed travel duration and activity–travel frequencies. Results from these analyses allowed us to test whether spatial accessibility affects travel time and travel frequency in opposite directions as hypothesized earlier. All modes were estimated in the statistical package Stata (7.0).

4.1. Accessibility and time use patterns of nonwork activities

In this part of the analyses, times spent in activity and in travel for the activity were combined for each of the eight activity types. This was based on a behavioral assumption that when an individual makes time use decisions, he/she first allocates time among different activities and then for each specific activity, he/she then splits between time spent in the activity itself and time for travel to reach the activity destination. Alternatively, one may assume that an individual allocates a relatively fixed amount of daily time for travel, i.e., the constant travel budget hypothesis (Zahavi and Ryan, 1980), and then distributes total travel time among travel for different activities.

Table 2 shows the SURE modeling results. Although the study focused on nonwork activities, the work activity model is also included. Discussions of the results for the nonwork models will occasionally refer to the work model in the context of work–nonwork activity interactions. Note that the $R^2$-values of the nonwork models are largely small, which is typi-
Table 2
Models of outside home activity participation

<table>
<thead>
<tr>
<th></th>
<th>Work (ln(P/F))</th>
<th>School (ln(P/F))</th>
<th>Shopping (ln(P/F))</th>
<th>Social (ln(P/F))</th>
<th>Personal business (ln(P/F))</th>
<th>Pick/drop (ln(P/F))</th>
<th>Other (ln(P/F))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Coefficient</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accessibility</td>
<td>0.011</td>
<td>1.00</td>
<td>0.021</td>
<td>0.980</td>
<td>0.031</td>
<td>0.653</td>
<td>2.420</td>
</tr>
<tr>
<td>Employment (full time)</td>
<td>0.906</td>
<td>73.06</td>
<td>-0.247</td>
<td>-21.26</td>
<td>0.014</td>
<td>-0.823</td>
<td>-10.72</td>
</tr>
<tr>
<td>Employment (part time)</td>
<td>0.571</td>
<td>34.95</td>
<td>0.111</td>
<td>0.79</td>
<td>0.052</td>
<td>0.407</td>
<td>-0.575</td>
</tr>
<tr>
<td>Household income</td>
<td>0.047</td>
<td>2.43</td>
<td>0.078</td>
<td>0.92</td>
<td>0.150</td>
<td>0.573</td>
<td>0.611</td>
</tr>
<tr>
<td>Age</td>
<td>-0.005</td>
<td>-0.75</td>
<td>-0.162</td>
<td>-32.48</td>
<td>0.009</td>
<td>10.57</td>
<td>-0.002</td>
</tr>
<tr>
<td>Vehicles per person</td>
<td>0.476</td>
<td>6.21</td>
<td>-0.882</td>
<td>-1.21</td>
<td>-0.36</td>
<td>-1.66</td>
<td>-0.017</td>
</tr>
<tr>
<td>Female</td>
<td>-0.320</td>
<td>-3.04</td>
<td>-0.684</td>
<td>-7.67</td>
<td>1.380</td>
<td>10.01</td>
<td>-0.280</td>
</tr>
<tr>
<td>With child under five</td>
<td>-0.462</td>
<td>-4.70</td>
<td>-0.973</td>
<td>-11.33</td>
<td>0.009</td>
<td>0.618</td>
<td>0.878</td>
</tr>
<tr>
<td>With driver's license</td>
<td>-0.009</td>
<td>-0.34</td>
<td>-0.620</td>
<td>-8.47</td>
<td>0.641</td>
<td>2.486</td>
<td>0.004</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.116</td>
<td>-26.54</td>
<td>-0.447</td>
<td>-11.40</td>
<td>-0.44</td>
<td>-10.14</td>
<td>-0.008</td>
</tr>
<tr>
<td>R²</td>
<td>0.578</td>
<td>0.256</td>
<td>0.078</td>
<td>0.017</td>
<td>0.036</td>
<td>0.017</td>
<td>0.045</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.568</td>
<td>0.235</td>
<td>0.078</td>
<td>0.017</td>
<td>0.035</td>
<td>0.017</td>
<td>0.043</td>
</tr>
<tr>
<td>N</td>
<td>5173</td>
<td>5173</td>
<td>5173</td>
<td>5173</td>
<td>5173</td>
<td>5173</td>
<td>5173</td>
</tr>
</tbody>
</table>

Magnitude of accessibility’s influence on activity participation

| Odd (95% CI) | 1.10 (0.96, 1.27) |

Note: The above figures show the odds of engaging in additional nonwork activity over staying home when accessibility increases by 1 standard deviation: odds = exp(coefficient ± standard deviation of accessibility).

× \text{p < 0.1.} \begin{align*}
\text{**: p < 0.05.} &
\end{align*}
cal in disaggregate modeling of time use (Levinson, 1999; Levinson and Kanchi, 2002). The follow-
ing highlight the main findings from the modeling results.

There were significant, positive relationships be-
tween spatial accessibility and time uses on school
and social activities, while other socio-economic and
demographic variables are controlled for. For per-
sonal business activities, the relationship was also
positive and significant at the 90% confidence level.
These positive correlations between accessibility and
activity participation are in accordance with common
knowledge: when services are easily accessible, peo-
ple are likely and able to consume more, resulting
in longer times spent in those services than other-
wise. The results were also consistent with those of
previous studies of similar types of activities (Bhat
and Gossen, 2003; Levinson, 1999). It is possible
that the observed positive correlations resulted from
individuals’ self-selection behavior—people who liked
to go shopping, participate in social activities, and
pursue plenty of personal business chose to live in
places with easy access to those service destinations.
In the latter case the urban form supplied places
with high accessibility to accommodate the demand
for nonwork activity for that portion of the popula-
tion.

Note that higher accessibility contributed to less
time devoted to pick up/drop off activities as in-
dicated by the negative coefficient of accessibility
in the Pick/Drop model. A plausible explanation is
that in high accessibility areas, for example, the
core area of the Boston region, activity destinations
were readily accessible by walking, cycling, public
transit, and other nondriving modes. Availability of
these travel alternatives made household members less
mobility-dependent on others. This finding suggests
that strategies to increase accessibility would yield cer-
tain transportation benefits by reducing chauffeuring
trips.

The roles of other socio-economic and demographic
variables in explaining time use are largely consis-
tent with previous studies reported in the literature
(Kitamura et al., 1997; Kostyniuk and Kitamura, 1986;
Niemeier and Morita, 1996; Robinson and Godbey,
1997). Full-time employment explained time uses with
statistical significance in all outside home activities.
An employed person, either full time or part time,
spends less time in shopping, social activities, or per-
sonal business than an unemployed person, mostly be-
cause a nonworker generally has more discretionary
time than a worker. The results showed that women re-
tained their traditional, family role by spending longer
times than men in shopping, personal business, chauf-
feuring family members, and other activities. A per-
son having young children of ages five or younger
spent more time in picking up or dropping off but
less time in school, social, and other activities. Pre-
vious studies have suggested that lower income people
tend to spend more time shopping to search for bet-
ter deals than higher income people (e.g., Levinson,
1999). This study found the relationship between
income and shopping duration insignificant. Never-
theless, the result did not contradict the findings of
previous studies. In this study, the probability of al-
locating time to shopping was estimated in reference
to the probability of staying home. Because the lower
income population also tends to spend more time at
home than those higher incomes, the ratios of proba-
bilities of shopping over staying at home became in-
distinguishable between the high and the low income
groups.

To explain the magnitude of the relationship be-
tween accessibility and nonwork activity participation,
it is useful to interpret the modeling results in some
quantitative terms (e.g., Rodriguez and Joo, 2004).
The last row of Table 2 shows the odds ratios of par-
ticipating in nonwork activities versus staying home.
Take the Social model as an example. A value of 1.23
indicates that for every standard deviation increase
in accessibility to social services opportunities in the
Boston region, the odds were 1.23 times greater for
people to engage in social activities than staying at
home, holding all other variables constant. Similarly,
with every standard deviation increase in accessibility
to school and personal business destinations, Bosto-
nians were, respectively, 1.20 and 1.14 times more
likely to participate in school activities and do per-
sonal business outside homes. In contrast, the odds
were 0.79 for them to spend time in chauffeuring fam-
ily members. No statistically significant relationship
was observed from the sample between accessibil-
ity and activity durations for shopping and other pur-
poses. For reference purposes, the odds ratios for the
two categories of activity were also calculated and re-
ported.
4.2. Accessibility, activity–travel duration, and activity–travel frequency

Study results presented in previous section have shown that higher accessibility was associated with more activities (in terms of time consumption) for school, social, and personal business purposes. What are the travel consequences of the increased activity participation resulting from improved accessibility? To answer this question, it is essential to understand the correlation between activity duration and travel time. If a person considers a specific activity important/attractive, she/he would spend more time in the activity and be willing to travel farther or longer in order to reach the activity. This implies a complementary, positive relationship between activity and travel duration. On the other hand, activity and travel both take time in the confines of 24 h a day. Increase in time use in one activity or travel means decrease in time for another. Therefore, activity and travel times may be substitutes. Which relationship dominates, complementary or substitution, depends on the purpose of the activity and travel. Furthermore, the relationship will likely vary depending on individual and household characteristics as well as the spatial and temporal context in which the activity takes place. A recent study by Schwanen and Dijst (2002) revealed quite a complex relation between work duration and commuting time in the Netherlands. Using national survey data, Levinson (1999) observed significant, positive relationships between travel and activity durations for all nonwork purposes except doctor visits. For work and returning home purposes, however, he found the relationships negative or substitution.

To explore the travel implications of time use characteristics related to accessibility in the Boston area, OLS regression models of travel times were estimated as functions of activity times, accessibility, and other socio-economic and demographic variables (Table 3). Expectedly, longer activity duration was significantly positively associated with travel duration for all other nonwork activities except for school activity. The insignificance of school activity duration in explaining travel time to school can be understood in that school activity duration is not entirely the outcome of individuals’ time allocation decision, but jointly determined by school schedules, for example, with fixed length of class sessions.

Accessibility displayed statistical significance in explaining travel times for two nonwork activities: shopping and social. For these two purposes, the estimated coefficients were positive, suggesting that higher accessibility leads to longer travel times for shopping and social activities. Examinations of the magnitude of accessibility’s influence showed that for every standard deviation increase in accessibility, there was an increase of 2.07 min in travel time for social activities and 1.20 min increase for shopping travel. It is worthy noting the effect of improving accessibility on commuting time to work. In the Boston sample, 1 standard deviation increase in employment accessibility was associated with 2.23 min decrease in one-way commute. This is consistent with Levinson’s (1999) study using national data and is in the same magnitude as what Shen (2000) found in his study of Bostonian’s commuting behavior and in his another study (Shen, 2004) using national data sets. The result indicates a substitution relationship between work and nonwork travel times: people tend to re-invest the times saved from shorter commute as a result of higher job accessibility into travel for other, nonwork activities. The result also is supportive to the constant travel time budget hypothesis (Zahavi and Ryan, 1988): individuals are likely to allocate a relatively stable amount of time for total daily travel and re-distribute times among different travel purposes to accommodate specific constraints associated with these activities.

Explanations to the positive association between accessibility and travel time for social and shopping activities lie in the dual effects of urban form on activity participation and travel. Recall that accessibility measures the spatial characteristics of the urban form combining the attractiveness of activity destinations (e.g., diverse choice of dining places) and spatial separation. If changes in accessibility were due to changes in destination attractiveness only, all else being equal, we would see no difference in travel times in accessing the destinations. On the other hand, if changes in accessibility resulted from reduced spatial separation and travel costs, we would see a reduction in time reaching the destinations on a single visit basis. However, higher accessibility, whether resulting from more attractive destination opportunities or from increased proximity, likely induces more frequent visits to activity destinations (Crane, 1996; Handy, 1996). When the induced effect dominates, we would see a positive correlation
### Table 3
Models of travel time for different activity purposes

<table>
<thead>
<tr>
<th>Activity purpose</th>
<th>Work</th>
<th>School</th>
<th>Shopping</th>
<th>Social</th>
<th>Personal business</th>
<th>Pick/drop</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>z-Stat</td>
<td>Coefficient</td>
<td>z-Stat</td>
<td>Coefficient</td>
<td>z-Stat</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Accuracy</td>
<td>-0.004</td>
<td>-1.07</td>
<td>0.009</td>
<td>1.50</td>
<td>0.062</td>
<td>1.37</td>
<td>0.079</td>
</tr>
<tr>
<td>Employment (full time)</td>
<td>-0.282</td>
<td>-4.47</td>
<td>-0.051</td>
<td>-0.45</td>
<td>0.711</td>
<td>2.05</td>
<td>0.459</td>
</tr>
<tr>
<td>Employment (part time)</td>
<td>5.136</td>
<td>2.42</td>
<td>-2.364</td>
<td>-0.87</td>
<td>-0.141</td>
<td>-0.01</td>
<td>1.340</td>
</tr>
<tr>
<td>Household income</td>
<td>2.814</td>
<td>3.02</td>
<td>-0.781</td>
<td>-0.47</td>
<td>1.209</td>
<td>1.31</td>
<td>1.222</td>
</tr>
<tr>
<td>Age</td>
<td>-0.021</td>
<td>-0.53</td>
<td>-0.048</td>
<td>0.51</td>
<td>0.017</td>
<td>0.04</td>
<td>0.046</td>
</tr>
<tr>
<td>Vehicles per person</td>
<td>-0.024</td>
<td>-0.16</td>
<td>0.198</td>
<td>0.15</td>
<td>-0.251</td>
<td>-0.29</td>
<td>-0.404</td>
</tr>
<tr>
<td>With child aged five or less</td>
<td>-7.939</td>
<td>-7.82</td>
<td>-0.013</td>
<td>-0.02</td>
<td>-0.318</td>
<td>-0.18</td>
<td>-2.266</td>
</tr>
<tr>
<td>With driver's license</td>
<td>-0.276</td>
<td>-0.10</td>
<td>3.445</td>
<td>1.32</td>
<td>1.712</td>
<td>0.78</td>
<td>0.052</td>
</tr>
<tr>
<td>Constant</td>
<td>31.57</td>
<td>6.04</td>
<td>24.79</td>
<td>3.01</td>
<td>8.06</td>
<td>1.58</td>
<td>4.11</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.048</td>
<td>0.012</td>
<td>0.027</td>
<td>0.074</td>
<td>0.081</td>
<td>0.070</td>
<td>0.045</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.045</td>
<td>0.000</td>
<td>0.021</td>
<td>0.070</td>
<td>0.045</td>
<td>0.017</td>
<td>0.247</td>
</tr>
<tr>
<td>N</td>
<td>3352</td>
<td>520</td>
<td>1732</td>
<td>21.57</td>
<td>1634</td>
<td>1706</td>
<td>796</td>
</tr>
</tbody>
</table>

Magnitude of accessibility’s influence on travel times:

| Time change (min) | -2.23 | -0.44 | 1.20 | 2.07 | 0.10 | -0.74 | 0.37 |

Note: The above figures show the changes in travel times (in minutes) as a result of 1 standard deviation increase in accessibility. The coefficients are multiplied by the standard deviation of accessibility.

- $p < 0.1$
- $** p < 0.05$
Table 4

Models of activity–travel frequency

<table>
<thead>
<tr>
<th></th>
<th>Work</th>
<th>School</th>
<th>Shopping</th>
<th>Social</th>
<th>Personal/business</th>
<th>Errand</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>t-stat</td>
<td>Coefficient</td>
<td>t-stat</td>
<td>Coefficient</td>
<td>t-stat</td>
<td>Coefficient</td>
<td>t-stat</td>
</tr>
<tr>
<td>Travel time</td>
<td>-0.045</td>
<td>0.016</td>
<td>-3.45</td>
<td>-0.006</td>
<td>-3.59</td>
<td>-0.004</td>
<td>-2.73</td>
</tr>
<tr>
<td>Accessibility</td>
<td>-0.001</td>
<td>-0.27</td>
<td>-0.003</td>
<td>-0.207</td>
<td>-2.63</td>
<td>-0.004</td>
<td>-2.46</td>
</tr>
<tr>
<td>Employment (full time)</td>
<td>0.073</td>
<td>3.81</td>
<td>0.485</td>
<td>2.92</td>
<td>0.46</td>
<td>0.014</td>
<td>-1.32</td>
</tr>
<tr>
<td>Employment (part time)</td>
<td>-0.233</td>
<td>-3.28</td>
<td>-0.207</td>
<td>-1.35</td>
<td>-0.125</td>
<td>-0.012</td>
<td>-0.143</td>
</tr>
<tr>
<td>Household income</td>
<td>0.242</td>
<td>3.38</td>
<td>-0.472</td>
<td>-2.10</td>
<td>0.229</td>
<td>0.013</td>
<td>0.043</td>
</tr>
<tr>
<td>Age</td>
<td>-0.005</td>
<td>-1.60</td>
<td>-0.014</td>
<td>-1.02</td>
<td>0.009</td>
<td>2.43</td>
<td>0.008</td>
</tr>
<tr>
<td>Vehicles per person</td>
<td>0.019</td>
<td>0.28</td>
<td>-0.003</td>
<td>0.24</td>
<td>-0.020</td>
<td>-0.25</td>
<td>-0.24</td>
</tr>
<tr>
<td>Female</td>
<td>-0.152</td>
<td>-4.77</td>
<td>0.404</td>
<td>1.64</td>
<td>0.111</td>
<td>0.56</td>
<td>0.072</td>
</tr>
<tr>
<td>With child aged five or less</td>
<td>-0.016</td>
<td>-0.93</td>
<td>0.416</td>
<td>1.56</td>
<td>0.052</td>
<td>0.50</td>
<td>-0.143</td>
</tr>
<tr>
<td>With driver's license</td>
<td>0.745</td>
<td>3.51</td>
<td>0.955</td>
<td>2.49</td>
<td>0.178</td>
<td>0.82</td>
<td>0.204</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test</th>
<th>p</th>
<th>Adjusted R²</th>
<th></th>
<th></th>
<th>Log likelihood</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>χ²</td>
<td>0.063</td>
<td>0.131</td>
<td>0.053</td>
<td>0.008</td>
<td>-1305.77</td>
<td>0.118</td>
<td>0.028</td>
</tr>
<tr>
<td>Adjusted χ²</td>
<td>0.000</td>
<td>0.118</td>
<td>0.028</td>
<td>0.004</td>
<td>0.009</td>
<td>0.000</td>
<td>0.030</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1305.77</td>
<td>-280.38</td>
<td>-1357.01</td>
<td>-1968.44</td>
<td>-1547.63</td>
<td>-392.10</td>
<td>-4786.51</td>
</tr>
<tr>
<td>N</td>
<td>3352</td>
<td>521</td>
<td>1734</td>
<td>2357</td>
<td>1638</td>
<td>884</td>
<td>3999</td>
</tr>
</tbody>
</table>

Magnitude of accessibility’s influence on activity–travel frequency

| Odds change (%) | -2.28 | -4.17 | 11.76 | 11.96 | -5.98 | 1.78 | 9.24 |

Note: The above figures show the percent changes in odds of making an additional trip when accessibility increases by 1 standard deviation. Odds change (%) = \( \exp(\text{coefficient} \times \text{standard deviation of accessibility}) - 1 \) \times 100.

* p < 0.05

** p < 0.01
between accessibility and total access times (not the times per trip). This was likely the case with the Boston data, in which travel times were the total of accessing activity destinations during the survey day.

To further test these explanations, a set of ordered logit models was estimated on trip frequency for non-work activities. The technique of ordered logit modeling is most commonly used in social and political sciences when the dependent variable is categorical or ordered—for instance, ‘poor,’ ‘good,’ and ‘excellent.’ It has also been applied to transportation in modeling the number of automobiles owned by a household, or the number of trips taken by an individual (e.g., Boarnet and Crane, 2001; Boarnet and Sarmiento, 1998; Crane and Crepeau, 1998). The estimated results indicate the odds of making an additional trip as a function of social, economic, spatial characteristics, and transportation characteristics.

Table 4 shows the results. For easy references, each model contains the same set of explanatory variables as in previous regression models. They include accessibility, average travel time per trip as a price variable, and other socio-economic variables. Notably, accessibility was positive, statistically significant to activity–travel frequency for school activities. All else being equal, 1 standard deviation increase in accessibility to schools contributed to 41.17% higher odds of making additional trips for school purposes. The observed higher frequency of travel for school purposes did not necessarily lead to longer total travel times as shown previously in Table 3. This finding suggests the net, positive benefits of improving spatial accessibility to schools: increasing school accessibility allows children and adults to pay more frequent visits to schools and spend more time in curricula, extra-curricula, and related activities in schools but do not have to spend longer total travel times for the activities.

Similarly, accessibility to opportunities in the social category was significant and positive; increase in accessibility by 1 standard deviation in accessibility to schools contributed to 41.17% higher odds of making additional trips for school purposes. The observed higher frequency of travel for school purposes did not necessarily lead to longer total travel times as shown previously in Table 3. This finding suggests the net, positive benefits of improving spatial accessibility to schools: increasing school accessibility allows children and adults to pay more frequent visits to schools and spend more time in curricula, extra-curricula, and related activities in schools but do not have to spend longer total travel times for the activities.

For activities in the category of personal business and pick up/drop off, no significant correlations were observed between accessibility and trip frequency. The last column in Table 4 shows the model for all nonwork purposes in general. The results confirm that a higher nonwork activity–travel frequency is associated with higher spatial accessibility.

5. Summary and conclusions

Persistent growth in travel demand challenges the traditional paradigm of analyzing travel behavior and calls for innovative ideas to help check the growing trend. While the proponents of the New Urbanism and Smart Growth anticipate reduction in driving demand by offering alternative urban form in communities and regions with better accessibility to spatial opportunities, the skepticism over the net transportation benefits of improvement in physical accessibility has generated much debate. This study explored the relationship between urban form and nonwork travel through time use analysis, a key element of the new paradigm for travel demand analysis that focuses on activity participation. Using data from the 1991 Activity–Travel Survey in Boston, the study tests the role of spatial accessibility as a composite measure of urban form in explaining: (i) individuals’ decisions to participate in nonwork activities; (ii) time spent in nonwork travel;
and (iii) frequencies of nonwork activities and travel. Differing from many existing studies that focused on specific types of nonwork travel, this study grouped outside home nonwork activities into six categories and examined individuals' activity participation and travel behavior as they relate to variations in spatial accessibility in an integrated time use framework.

The results showed varying effects of modifying spatial accessibility on nonwork activity participation among different activity categories. Higher accessibility was associated with more nonwork activities for school, social, and personal business purposes. A significant, negative correlation was observed between levels of accessibility and amount of time spent in pick-up/drop-off, suggesting the potential benefits of improving accessibility to save cost and time from less chauffeuring activities. The study found no significant relationship between accessibility and amount of times spent in shopping, civic, religious, and other activities.

When accessibility changed, travel time and trip frequency also changed. These changes, however, were not all the same among various activity purposes. As a result, the net travel outcome associated with changes in accessibility also differed among different types of activity and travel. When accessibility to schools improved, children and adults were found to pay more visits to and spent more times in schools yet without generating additional total school travel. This finding suggests the positive net benefits associated with improvement in physical access to schools, supporting any programs and initiatives, for example, the Safe Route To School program recently implemented in several states that help enhance school access.

There was a substitution relationship between work commute and nonwork travel when levels of accessibility changed. The study found that an increase in accessibility by 1 standard deviation was associated with a decrease in work commute by 2.23 min, but increases in travel times for social activities by 2.07 min and for shopping travel by 1.20 min. The increase in social travel was due to more frequent trip making resulting from higher accessibility. Note that social activities had the largest time share among all nonwork activities, averaging 72.09 min in the Boston sample (Table 1). These increases in travel time and frequency may lead to more undesirable transportation and environmental consequences, for example, increased road congestion and air pollution (due to more frequent cold-starts of vehicle operation). As a result, the potential positive benefits of accessibility enhancement may be offset from a societal perspective.

One solution to reducing this offsetting effect would be to encourage modal shift from driving to nondriving modes. If the increased travel demand induced by higher accessibility can be met by alternatives to driving such as walking, bicycling, and transit, the net transportation benefits of enhancing spatial accessibility to destinations for social activities would be positive. To this end, the study results underscore the importance of landscape architecture, environmental design and physical planning of cities and regions to achieve transportation objectives. Through their professional practice, landscape architects, designers, and physical planners should help develop an urban form that is friendly to pedestrians and cyclists and supports transit operations and services. With this urban form, efforts to further improving spatial accessibility would yield positive transportation benefits rather than induce more driving.

References


Ming Zhang is currently an assistant professor in the Community and Regional Planning Program in the School of Architecture, the University of Texas, Austin. His research and teaching interests include urban transportation planning, mobility/accessibility and urban form, and GIS applications in planning. Prior to joining UT Austin, Ming Zhang held several academic and professional positions, including tenure-track assistant professor in the Department of Landscape Architecture and Urban Planning at Texas A&M University, research scientist at the Rockefeller Institute of Government in Albany, New York, and lecturer and licensed planner/designer at the Huazhong (Central China) University of Science and Technology. He has published in such journals as The Journal of American Planning Association, Transportation Research Record, and The China City Planning Review. Ming Zhang holds the degrees of PhD in Urban and Regional Planning and Master of Science in Transportation (both from MIT), Master of Regional Planning (from SUNY Albany), and Master of Urban Planning & Design and Bachelor of Architecture (both from Tsinghua University, Beijing).