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Moving from trip-based to activity-based measures of accessibility

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Abstract

This paper studies the properties and performance of a new measure of accessibility, called the activity-based accessibility (ABA) measure, and compares it to traditional measures of accessibility, including isochrone, gravity and utility-based measures. The novel aspect of the ABA is that it measures accessibility to all activities in which an individual engages, incorporating constraints such as scheduling, and travel characteristics such as trip chaining. The ABA is generated from the day activity schedule (DAS) model system, an integrated system based on the concept of an activity pattern, which identifies the sequence and tour structure among all the activities and trips taken by an individual during a day. A byproduct is an individual's expected maximum utility over the choices of all available activity patterns, and from this the ABA is derived. The ABA is related to the logsum accessibility measures frequently derived from destination and

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mode discrete choice models. The key difference is that it is generated not by examining a particular trip, but by examining all trips and activities throughout the day.

A case study using data from Portland, Oregon, demonstrates the rich picture of accessibility made available by use of the ABA, and highlights differences between the ABA and more traditional measures of accessibility. The ABA is successful in (a) capturing taste heterogeneity across individuals (not possible with aggregate accessibility measures), (b) combining different types of trips into a unified measure of accessibility (not possible with trip-based measures), (c) reflecting the impact of scheduling and trip chaining on accessibility (not possible with trip-based measures), and (d) quantifying differing accessibility impacts on important segments of the population such as unemployed and zero auto households (not possible with aggregate measures, and limited with trip-based measures).

1. Introduction

"Accessibility", although a widely used term in the transportation-planning arena, is an abstract concept. Researchers have defined this term in various ways and have constructed numerous mathematical formulations to measure its value. Accessibility is essential to evaluate the interrelationships between patterns of land use and the nature of transportation systems. Therefore, indexes of accessibility that describe the correlation between land use patterns and transportation systems have been used extensively by researchers and policy makers, especially in assessing the existing transportation system and forecasting its performance. One definition of accessibility (U.S. Department of Environment, 1996) is "the ease and convenience of access to spatially distributed opportunities with a choice of travel". The difficulty is how to quantify this "ease and convenience," which is particularly complex as it is a function of varying types of trips and activities and most likely varies across people according to their tastes and preferences.

This paper proposes a new measure of accessibility, the activity-based accessibility or ABA. The novel aspect of the ABA is that it is a measure of accessibility to all activities in which an individual engages, incorporating constraints such as scheduling, and travel characteristics such as trip chaining. Such a measure is significantly different from the traditional trip-based measures of accessibility, which focus on one trip purpose and do not incorporate scheduling or trip chaining. The paper proceeds by first describing traditional measures of accessibility, then presenting the activity-based accessibility, and finally presenting results of a case study using data from Portland Oregon.

2. Traditional measures of accessibility

A key property of measures that have traditionally been used to quantify accessibility is that they are "trip-based", meaning they only examine one trip type at a time (for example, the work trip) and do not consider scheduling or trip chaining. Such measures are briefly described in this section. Following Handy and Niemeier (1997), accessibility measures are often classified into three categories: isochrone, gravity-based and utility-based.

Isochrone measures are also referred to as ‘‘cumulative opportunity’’ measures. Early examples include Wachs and Kumagai (1973) and Vickerman (1974). They count the number of opportunities that can be reached within a given travel time, distance, or generalized cost as shown by the following equation:

$$\mathrm{Acc}_i = \sum_j W_j a_j, \tag{1}$$

where a_j represents the opportunities in a zone j; W_j equals 1 if $c_{ij} \leqslant c^*_{ij}$, and 0 otherwise; c_{ij} is a measure of impedance between zones i and j, and c^*_{ij} is the pre-determined range within which the activity opportunities are counted.

An example of an isochrone measure is the ‘‘total number of employment opportunities within 30 minutes by transit’’. The strengths of this measure are that it is easy to compute and understand. However, this measure of accessibility is highly sensitive to the size of the range (in the example, 30 minutes) and the representation of opportunities (in the example, total employment), both of which are difficult to determine.

Gravity-based measures are so called because they are derived from the denominator in the gravity model for trip distribution. It was first derived by Hanson (1959), and used in various analysis, including Huff (1963) and Geertman et al. (1995).

A generic formulation of gravity-based measures to calculate the accessibility of zone i is

$$\mathrm{Acc}_i = \sum_j a_j f(c_{ij}), \tag{2}$$

where j indexes the available destination zones that are reachable from zone i; a_j measures the activity opportunities in zone j, and $f(c_{ij})$ is an impedance function of traveling from zone i to zone j.

The isochrone measure is a special case of gravity in which $f(c_{ij})$ is equal to 1 within the range defined to count the activity opportunities, and 0 outside that range.

Although any number of formulations of $f(c_{ij})$ are possible, in many cases it includes the travel time in a negative exponential form; the farther away an opportunity, the lower is its impact on accessibility values. In this way, the gravity-based measures represent the joint effect of transportation systems (captured using $f(c_{ij})$) and land use patterns (captured by a_j) on accessibility. The limitation of the gravity measure is that it neglects the variations across individuals. For example, a gravity measure says that a retired grandfather and his college student grandson who live together each have identical values of accessibility.

Utility-based measures (see, for example, Neuburger, 1971 or Ben-Akiva and Lerman, 1977) are based on random utility theory (see Domencich and McFadden, 1975). Random utility theory assumes that people select the alternative with the highest utility. However, utility is not known with certainty to the analyst, and therefore is treated as a random variable. The utility of an alternative has two additive components. One is called systematic utility, consisting of observable attributes of the alternative and characteristics of the decision-maker that are assumed to impact the decision. The other component is called the disturbance, representing the unobservable portion of the utility. In order to obtain a tractable form, often the disturbances of all alternatives are assumed to be identically and independently Gumbel distributed with a scale parameter μ—giving the model the familiar multinomial logit (MNL) form—and each alternative's systematic utility and disturbance are combined additively. For MNL, an individual's expected maximum utility achieved from a set of alternatives can be expressed as:

$$E(\max_{i \in C_n} U_{\text{in}}) = \frac{1}{\mu} \ln \sum_{i \in C_n} \exp(\mu V_{\text{in}}),$$

where V_{in} is the systematic component of utility U_{in} for individual n choosing alternative i from the choice set C_n. For the more general nested logit model (NL) the expected maximum utility is also the "logsum", but it is calculated for the root, or highest, level of the model, which includes in it the logsums from the lower levels. Even more generally, for the generalized extreme value (GEV) model, of which MNL and NL are the most common special cases, the expected maximum utility achieved from a set of alternatives can be expressed as:

$$E(\max_{i \in C_n} U_{\text{in}}) = \frac{1}{\mu} \ln G, \tag{3}$$

where G is the function that characterizes the particular form of the GEV model (McFadden, 1978; Ben-Akiva and Lerman, 1985).

Utility-based accessibility measures use this expected maximum utility from a random utility model as the measure of accessibility, because it represents the expected "worth" of a set of travel alternatives. Usually, such measures are derived from a multinomial model of destination choice or a nested logit model of destination and mode choice. An advantage of utility-based measures is that they can represent accessibility at an individual level according to individual preferences (Pirie, 1979) and in this way capture taste differences. Another advantage is that the expected maximum utility can be derived from any choice situation, thus an accessibility measured from a destination-mode choice model can capture the impact of all modes including auto, transit and non-motorized options on accessibility. It is this type of extension that is exploited in the activity-based accessibility presented in this paper.

3. Activity-based accessibility

The activity-based accessibility measure is derived from random utility theory, and therefore also belongs to the class of utility-based accessibility measures discussed above. The major contribution of the ABA measure is that it incorporates the impact of trip chaining, the full set of activities pursued in a day, and the scheduling of activities. This is different from the traditional utility-based measures, which focus on a particular trip purpose, without trip chaining, and without incorporating the time dimension.

The activity-based accessibility measure was first presented in Ben-Akiva and Bowman (1998). It is generated from the day activity schedule (DAS) model system, which is an activity-based travel demand model system, and therefore we refer to the resulting measure of accessibility as the "activity-based accessibility" (ABA). Rather than modeling each trip separately or as a part of a tour, the DAS models the whole day's schedule of multiple activities and trips taken by an individual, using various modes, and joined together in a particular pattern. The intent is to capture more realistically people's travel and activity behavior.

3.1. The day activity schedule model system

The day activity schedule model system was proposed by Ben-Akiva et al. (1996), and first implemented using data from Boston (Bowman, 1995; Bowman and Ben-Akiva, 2001). It was enriched in Portland, Oregon, by Bradley et al. (1998), and further refined by Bowman (1998). The DAS model regards the activities conducted in a whole day as the basis for modeling travel behavior. This is based on the idea that the need to travel is derived from people's desire to pursue various activities, and that activities conducted throughout a day are inter-related.

The DAS model defines the concepts of *activity pattern* and *activity schedule*. Activity pattern refers to the set of activities and tours (that is, journeys beginning and ending at the same location) taken by an individual during a day. It identifies the purposes of the activities, identifies one of them as primary, and locates each activity either at home or on a particular tour. The activity schedule refers to the activity pattern, and adds detailed information about the pattern's tours, such as the sequence, timing and location of activities, as well as the travel modes. Thus, the activity pattern identifies the basic framework of a person's day, and the activity schedule fills in the details.

For the analysis presented here, a published implementation of the DAS model is used. It is the second implementation used by Portland, Oregon, to model and forecast people's travel in the Portland metropolitan area. In the Portland implementation, each activity pattern is defined by the following five items: (a) the primary activity of the day, (b) whether the primary activity occurs at home or away from home, (c) the type of tour for the primary activity, including number, purpose and the sequence of activity stops, (d) the number and purpose of secondary tours, and (e) purpose-specific participation in at-home activities. The activity schedule consists of five levels of choices. The highest level is the choice of day activity pattern. Proceeding downward, the other levels include time of day for home-based tours, destination and mode for home-based tours, work-based sub-tours, and intermediate stop locations for car driver tours. Upper level choices condition the lower level choices, and the available lower level alternatives inform the upper level choice with the expected maximum utility. The activity pattern sub-model includes terms in its utility function representing the expected utility of tours in the pattern. The lower level models describe the choices among travel options, including the travel time, mode and destination, and work-based sub-tours.

3.2. The activity-based accessibility measure

The ABA measure obtained from the DAS model system is defined as the expected value of an individual's maximum utility among the available activity schedules, given his or her residential location. Its key aspects are that (a) it reflects the outcome of travel and activity scheduling, (b) it captures the relative attractiveness of various alternatives for activity participation, trip combination, travel mode, and timing, and (c) it reflects not only the nature of land use and properties of the transportation system, but also the socioeconomic characteristics of individuals. It thus departs substantially from the traditional trip-based measures.

Activity-based accessibility belongs to the utility-based measures of accessibility, where accessibility is defined as the expected maximum utility over a choice situation faced by an individual, and formulated as in Eq. (3). The key to the ABA is that the choice set C_n is a set of activity schedules, each describing in detail one option for conducting all the activities and travel of an entire day.

There is a technical detail that is of utmost importance to consider when using utility-based measures, whether they are the traditional measures derived from destination choice or the more complex ABA presented here. Therefore, we spend significant time discussing such details in this paper. The issue is that the expected maximum utility derived from a choice model is not, in general, in a form that is directly comparable across individuals. In order to make comparisons across individuals or to generate summary statistics based on the ABA measure (or any utility-based measure), two conditions must be satisfied: one is called the "scale condition", and the other is called the "level condition". The scale condition requires all the calculated accessibility values to share the same scale or same unit. It is needed because the units of the ABA match those of V_{in}, and these units vary across individuals. The level condition requires the ABA values to have a consistent benchmark utility. This is necessary because the underlying random utility model does not depend on the absolute size of utility but on the utility differences of the available alternatives. It is well understood that any constant could be added to all alternatives' utilities without changing the choice model probabilities. However, it is important to note that the addition of a constant does, indeed, change the accessibility as calculated by Eq. (3). For further explanation of the properties of utility-based accessibility measures see Ben-Akiva and Lerman (1985). The key idea is that the accessibility measure must be normalized, ensuring that both the scale and level conditions are satisfied, before comparisons can be made across individuals and summary statistics can be generated.

A standard method for dealing with the level condition is to compute the differences in accessibility resulting from the application of a transportation-related policy. In this way, the benchmark utility of each individual cancels out while computing the difference. If Acc_n^b denotes the accessibility value for individual n before imposing any transportation policy, and Acc_n^a denotes the same measure but after imposing the transportation policy, then the change in accessibility from the policy is

$$\Delta\text{Acc}_n = \text{Acc}_n^a - \text{Acc}_n^b. \tag{4}$$

The scale condition can be satisfied by converting the units of ΔAcc_n from utility units to those of a model variable (x) that is comparable across individuals, through the use of a conversion factor (α_{nx}) defined in terms of x. The result,

$$\Delta\text{Acc}_{nx} = \Delta\text{Acc}_n/\alpha_{nx}, \tag{5}$$

is a normalized measure of accessibility, expressed in the units of x, that can be compared across individuals. In transportation policy analysis it is customary to use as x either travel time or cost.

An empirical method can be used to develop the conversion factor by calculating the difference in utility that occurs when the travel time (or cost) of all trips in all of the available activity schedules is incremented by Δx. Specifically, we use

$$\alpha_{nx} = \frac{\text{Acc}_n^{b(\Delta_x)} - \text{Acc}_n^b}{\Delta x \sum_{i \in C_n} p_{\text{in}} t_i}, \tag{6}$$

where $\text{Acc}_n^{b(\Delta_x)}$ represents n's accessibility when x is increased by Δx in every trip of every available activity schedule; p_{in} is n's probability of activity schedule i, and t_i is the number of trips in activity schedule i.

The numerator of Eq. (6) is the change in expected utility induced by the increase in time or cost, and the denominator is the change in the expected time or cost itself. In practice, the numerator and denominator are calculated simultaneously in a nested calculation that accounts for the travel attributes of all available activity schedules. The conversion factor can be thought of as an empirical approximation of the marginal utility with respect to travel time or cost, taking into consideration all available activity schedules.

While we are focused on accessibility in this paper, note that the formulation presented in Eq. (5) can also be interpreted as the change in consumer surplus (see Ben-Akiva and Lerman, 1985, for more information). For example, in the case of a peak period toll used later in the case study, when x is travel cost, $\Delta\mathrm{Acc}_{nx}$ is the change (loss) in consumer surplus expressed in cost units caused by the imposition of the toll.

As a summary, in order to study some region's residents' accessibility capturing their whole day activities, using this proposed ABA measure, one needs to follow these steps: first, collect data of the whole day activity information for all the residents; second, develop the DAS model that describes each individual's whole day activity scheduling in a hierarchical structure (Bowman, 1998); third, plug in the parameter estimates from the DAS model in the second step, compute the logsums until the very top of the hierarchy. This will obtain Acc_n for every decision maker in this study. Finally, following Eqs. (4)–(6), the normalized measure of accessibility $\Delta\mathrm{Acc}_{nx}$ can be computed and is ready to use for further analysis across individuals.

3.3. Relationship to other activity-based accessibility measures

Other measures of accessibility exist that are also based on the idea of access to activities. Kwan et al. (2003), Miller (1991), Kwan (1998), Ashiru et al. (2003), and Chen (1996) identify accessibility measures that are based on the time-geographic perspective (Hägerstrand, 1970), employing space–time constraints and the space–time prism (Lenntorp, 1976 and Burns, 1979). The accessibility measure can be defined either as a simple function of the feasible opportunity set, such as cardinality of the set or weighted sum of the opportunities, as in Miller (1991) and Kwan (1998); or as the expected maximum of the utilities for all possible opportunities. Chen's measure is derived directly from a mathematical programming formulation proposed by Recker (1995), where the objective is to minimize the total travel time and waiting time for all the activities engaged by all the household members, subject to constraints related to time, the physical action space, the available vehicles, trip chaining, and interactions among household members.

A key difference between the activity-based accessibility measures in the literature as described above and the ABA measure presented in this paper is that the measures in the literature treat important attributes of the activity pattern as exogenous. The exogenous attributes include participation, location and duration of all "mandatory" activities (and in some cases all activities), as well as the travel mode for all trips (which is assumed to be the same for all trips of all persons). Such measures of accessibility depend on the activity opportunities that can be reached for the "non-mandatory" activity stops. Differences in accessibility across individuals or households depend primarily on differences in the number, timing and location of the exogenous activities (although Chen's measure also depends on the household's vehicle fleet), and the cost and travel speed of the assumed travel mode. In contrast, the measure proposed in this paper treats activities endogenously via a microeconomic approach based on specifying utilities of activity participation.

4. Empirical analysis of the ABA

4.1. Introduction

Thus far, we have presented a technical discussion of the ABA in which we suggest that the ABA improves upon traditional measures of accessibility by calculating accessibility as a function of all activities pursued throughout the day, including issues such as trip chaining and scheduling. This departs substantially from traditional trip-based measures, which focus on accessibility for a particular purpose such as work or shopping, and do not consider trip chaining or scheduling. Also important, the ABA, like all utility-based accessibility measures, can capture taste heterogeneity. In this section, we present a case study that further explores these issues and the properties of the ABA. The case study uses data from Portland, Oregon, and the DAS model system as described above. Accessibility is examined using a 10% synthetic population (55,000 households, 105,506 individuals over 16), which was generated by Portland Metro for their planning purposes. Note that, unless otherwise noted, all values of accessibility are calculated in reference to a particular residential location, but not in reference to a particular work location. This is in accordance with the manner in which traditional accessibility measures are calculated, but is not necessary with the ABA, as will be shown in the empirical results. Note also that the Portland DAS model (and hence also the normalized ABA), in calculating expected utility logsums of the available day activity schedules, uses travel time and cost information from the tours in the schedule without incorporating travel time and cost information from the intermediate stops of the tours. This simplification of the DAS approach causes the empirical results to only partially reflect the conceptual advantages of the ABA discussed in this paper.

There are two main factors that influence accessibility: the space dimension and the individuality dimension. For example, the accessibility of a zone in the suburbs is lower than the accessibility of a zone downtown. Further, the accessibility of any particular zone is perceived differently by, for example, a single college student versus a married couple with children, because they have different preferences regarding activities and schedules. In the empirical study, we will explore both of these dimensions. In particular, we perform the following analyses, each described in more detail in the sections that follow:

First, we explore the variation across the population of a peak period toll's accessibility impact. This is done by first using Eq. (5) to calculate the loss of accessibility for each individual in our 10% sample, and then plotting the distribution of these losses. We will see that the magnitude of impact varies significantly across the population.

Second, we further explore the impact of the peak period toll by plotting the distributions by market segments, where the market segments are defined by auto ownership and employment. Such analysis is critical if one is interested in issues of environmental justice such as who is impacted by a given policy and by how much.

Third, we explore how taste heterogeneity leads to different values of accessibility even when people are faced with the same land use pattern and transportation system. This is done by generating accessibility plots of the Portland area (high accessible zones versus low accessible zones) based on different demographic characteristics. The ability to capture such heterogeneity is an example of analysis that is not possible with aggregate accessibility measures such as isochrone and gravity.

Finally, we compare accessibility plots generated by the ABA with those generated by a traditional trip-based utility measure derived from a destination-mode choice model. The focus here is to determine the added benefit, if any, of reflecting in the accessibility measure all activities throughout the day.

Through the analysis, we aim to reflect the rich picture of accessibility made available by use of the ABA, and highlight differences between the uses of the ABA versus more traditional measures of accessibility.

4.2. Variation of accessibility (ABA) impacts resulting from a peak period toll

In the first empirical experiment, we study the impact of a peak-period toll (50 cents/mile in the morning and evening peak) on accessibility.[4] Since people have different residential locations as well as heterogeneous tastes, the impact of the toll will vary across the population. Fig. 1 shows the distribution across the population of the decrease in accessibility resulting from the peak-period toll. The change in accessibility is calculated for each person in the 10% sample using Eq. (5), and the distribution is displayed with both time units and monetary units.

Both of the plots have a similar bimodal shape with a smaller peak to the left of the larger peak, and both plots have long tails to the right. An analysis of the individuals that make up each mode indicates that the smaller peak consists of unemployed people and the larger peak consists of employed people. This matches a priori beliefs, because we expect unemployed people to be less affected by a peak hour toll. This could be for a number of reasons, including that they take fewer trips during the peak period, they have more flexibility to adjust the timing of their trips, or they have a lower value of time and so are less impacted by switching to a slower mode. All of these types of adjustments are captured (to some extent) in the DAS model system, and therefore are reflected in the ABA measure. This is no minor point that the ABA is able to directly quantify the differing impact of the peak-period toll to employed and unemployed persons, which is not possible to quantify using any of the other accessibility measures presented in this paper. This suggests that the ABA measure can provide valuable insight to issues of environmental justice and other policy issues.

To further explore the characteristics of the individuals, we use the marginal utilities of cost and time used in the accessibility calculation to generate the value of time (VOT) distribution in the population, which is shown in Fig. 2.

This VOT distribution suggests two distinct groups of people. The larger group consists of 75% of the population, among which the VOT are distributed with two modes, at approximately \$6.40/h and \$7.80/h respectively. The smaller group has a single mode at \$12.40/h. An examination of the socioeconomic characteristics of individuals in the proximity of each of the three modes, finds that the average income is \$20.6k for the first mode, \$40.5k for the second mode and \$91.0k for the mode with the highest value. This further validates that the ABA measure produces reasonable results (value of time increases with income), and also provides valuable information on VOT as a byproduct of the ABA calculations.

[4] We only studied the direct effect of the peak hour toll, which includes travelers' adjustments in their activity schedules, but not the indirect effects such as decreased travel time due to reduced traffic congestion. These could be captured by equilibrating the DAS model with a traffic equilibrium model before recalculating the ABA.

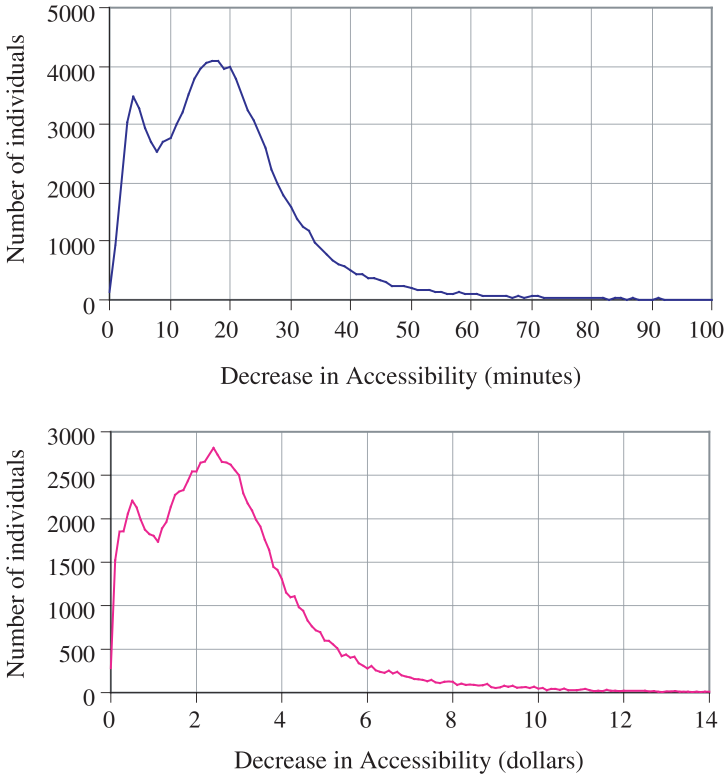

Fig. 1. Distribution of the loss of accessibility as a result of a peak-period toll.

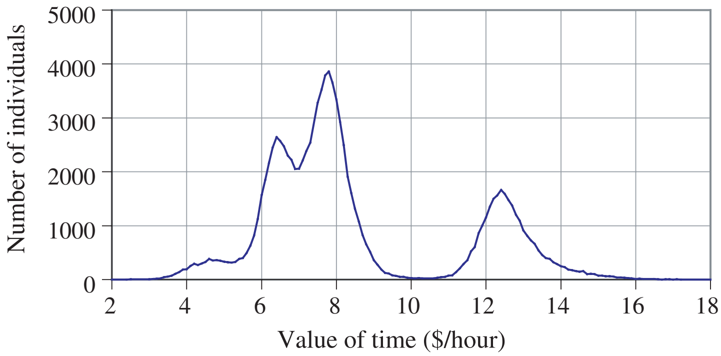

Fig. 2. Distribution of value of time in the population.

4.3. Variation of accessibility (ABA) impacts by market segment resulting from a peak period toll

We further explore the sensitivity of the ABA measure to social and economic variables by examining the impact of a peak period toll for different market segments. For the analysis, we plot the distributions shown in Fig. 1 for market segments based on auto ownership and employment

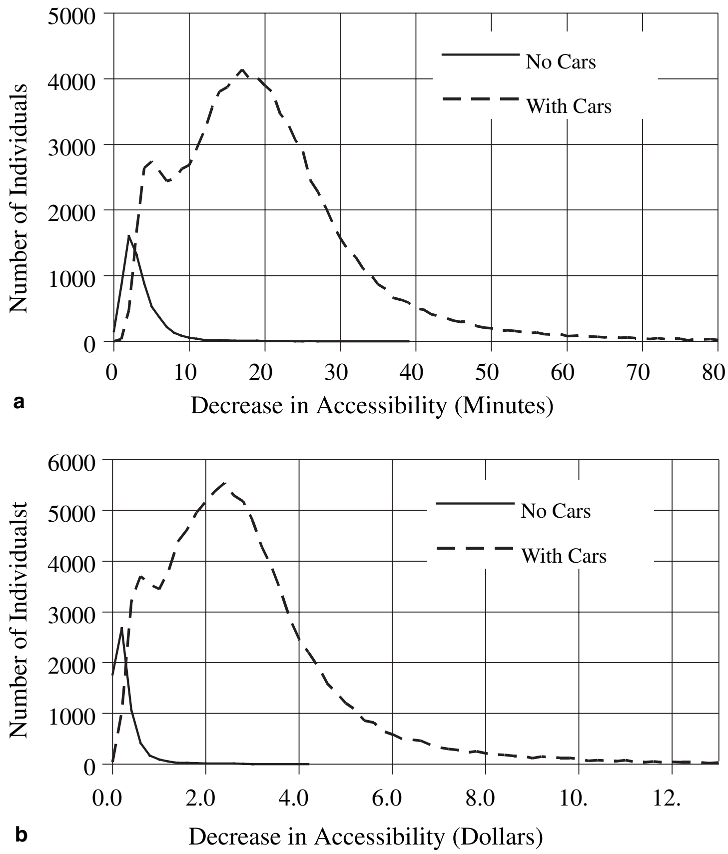

Fig. 3. Distributions of the loss of accessibility for persons with and without cars.

status. Fig. 3 displays the sensitivity of market segments defined by auto ownership to the peak-period toll. About 6% of the persons in the data do not own a car. Not surprisingly, the plots indicate that individuals who do not have cars are significantly less impacted by a peak-period highway toll than those who do.

Fig. 4 displays the distributions for segments based on employment status. Similar to the results for the people without cars, unemployed people are significantly less impacted by the imposition of a peak-period toll for reasons discussed above.

This sensitivity analysis of changes in accessibility as a result of the peak-period toll with respect to these market segments indicates that the ABA is able to reflect the impact of socio-economic factors such as auto ownership and employment status. Importantly, it does so by linking the socio-demographic characteristics to propensities for certain types of day schedules as well as different cost- and time-sensitivities.

4.4. Variations of accessibility (ABA) across space, fixing demographics

All of the calculations above were made using the individuals' residence zones as the anchor from which to calculate a single value of accessibility for each person. In this subsection, we

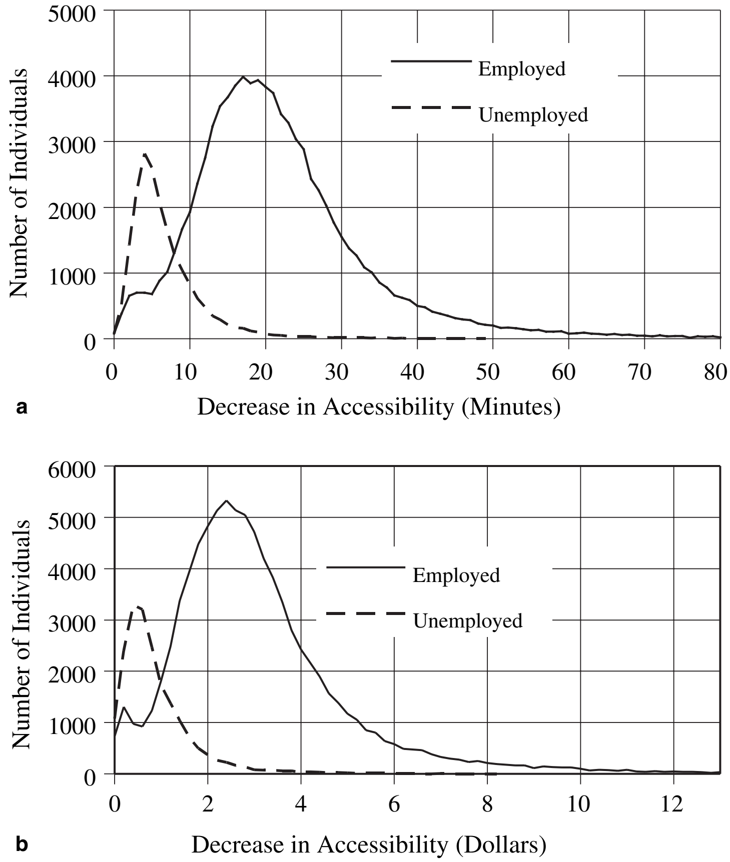

Fig. 4. Distributions of the loss of accessibility for employed and unemployed persons.

examine how accessibility of an individual varies throughout the urban area by calculating accessibility across all zones for an individual. Note that the normalization (and the application of a peak-period toll) is not necessary in this case, because we are examining one individual at a time and examining the relative accessibilities of zones. The objective is to examine how accessibility varies over space and how demographics affect this spatial variation.

For the experiment, we start by examining the spatial accessibility of a 25-year-old male who lives with his 26-year-old wife. He has a full time job, and his wife does not work. They have two cars (and both have driver's licenses), no children, and an annual income of $50,000 (medium income). First we will perform a long-term analysis in which his work location is not known. Given the characteristics of this individual, his accessibility as calculated for each zone in the urban area is plotted in Fig. 5a.[5]

[5] TransCAD was used to generate these plots.

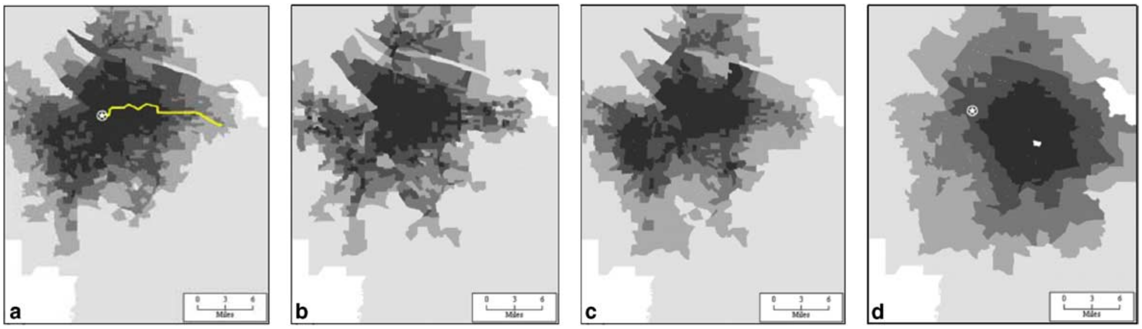

Fig. 5. Variations of accessibility across space (within each plot) and across socio-economic characteristics (across the plots).

As with every map in this section, this map displays five different levels of accessibility: the darkest shade represents the zones that are amongst the 20% with highest accessibility, the lightest shade represents those zones amongst the 20% with lowest accessibility, and there are three shades in-between representing the other three quintiles. The shading pattern represents the relative attractiveness in terms of accessibility of each zone as a residential location. The white star in map Fig. 5a marks the central business district (CBD) of Portland, and the line starting from the CBD and extending to the east is the route of the Metropolitan Area Express (MAX), the light rail system in Portland. The highest accessibility for this individual occurs near the CBD and MAX. There are also high accessibility zones to the southwest of the CBD, near two major activity centers where a large shopping mall and public park provide many maintenance and recreational activity opportunities.

Next, to investigate how demographics impact the individual accessibility across the urban area, we vary some of the individual characteristics and reexamine the accessibility plots. Fig. 5b displays the accessibility plot for the same individual as in Fig. 5a with the exception that we now assume that the household no longer has a car. Note that the two activity centers in the southwest of the urban area lose much of their attractiveness due to a relatively lower level of transit service in that area. The high accessibility region is now almost solely oriented around the CBD and the light rail transit line, and in general areas of high density.

Fig. 5c displays the accessibility plot that results when the household has a car again; however now both members of the family are unemployed. Again, the most obvious difference is around the two activity centers. The plot shows a relative decrease of accessibility oriented towards the center of the city where the job density is highest, and more oriented to the activity centers, which provide access to services and shopping albeit at a lower overall development density.

Additional studies were conducted by changing other characteristics, such as income, age and number of children, and all such adjustments led to deviations from the base case. Those displayed in Fig. 5a–c are those with the most visually significant changes, and presumably those that have the greatest impact on accessibility.

The final plot in Fig. 5 displays a short-term measure of accessibility, in which it is assumed that the individual has a fixed work location in the white zone in the right-center of the map. When the work location is known, the perception of overall accessibility is highly tied to ease of access to work, indicating the significance of the work trip in the overall accessibility picture. Nonetheless, note how the most accessible zones are not centered solely on the work location, but are heavily skewed towards the high density parts of the city. This indicates that while the work trip is important, measures of accessibility based solely on the work trip alone are not adequate. Furthermore, while traditional trip-based measures require each purpose to be analyzed separately, the ABA provides a means of weighting the importance (or trade-offs) of these various types of activities in the calculation of a single measure of accessibility.

The conclusion from this analysis is that both socio-demographic characteristics as well as multiple types of activity purposes have significant influence on perceived accessibility, and the ABA has the ability to capture such factors.

4.5. Comparison of ABA accessibility to a traditional utility-based accessibility measure

So far we have only examined the ABA in the case study. This section compares the ABA with a traditional trip-based measure of accessibility (we will denote as TBA) derived from a work destination-mode choice model. In this analysis, our TBA is derived from the work destination-mode choice model that is a component of the DAS from which the ABA is derived. Both the ABA and the TBA are based on random utility theory, both are disaggregate measures, and both have an underlying disaggregate travel choice model. The key difference between these two measures is that the TBA measure considers only one single trip (the work trip), with one purpose, choosing one destination and mode at a given time, with no consideration of trip chaining. Recall that the ABA measure is generated from the full DAS model system, which describes the whole day travel schedule and considers multiple trips conducted at different time periods of a day. Therefore, as we saw earlier, the ABA is able to reflect the influence of different types of trips and their scheduling on accessibility. As the TBA measure can consider only a single trip, we choose to use the work trip because, as evidenced above, it is the most important trip purpose impacting accessibility. Due to this restriction, we perform our comparison of the two measures using only those persons in the sample who are employed.

The TBA, like the ABA, is sensitive to socio-economic effects. However, since this particular aspect is not the emphasis of this portion of the analysis, we attempt to disentangle the effect of socio-economics. Our approach is to randomly select 100 individuals from among the employed individuals in the sample. We then calculate accessibility using both the ABA and TBA for each individual and in each zone in the urban area, and average the accessibility values computed for each zone by each measure. In order to compute the average values across different individuals, both the ABA and TBA have to be normalized as described above. Again, the same peak hour toll described above is imposed.

The first level of analysis is to compare the change in accessibility histograms and basic statistics resulting from the two measures, which are shown in Fig. 6. The histograms are similarly skewed to the left with a long tail to the right, a unimodal distribution and a fairly flat peak. The primary difference is that the TBA histogram has a lower peak, and is shifted to the right of the ABA histogram.

It is significant that the ABA measure shows an overall lower accessibility impact from the peak-period toll. The reason for this is the difference in how the ABA and TBA are affected by a policy that is limited to the peak period, when most work trips occur. Unlike the TBA, which considers only the work tour and accepts as fixed the activity pattern and schedule in which the

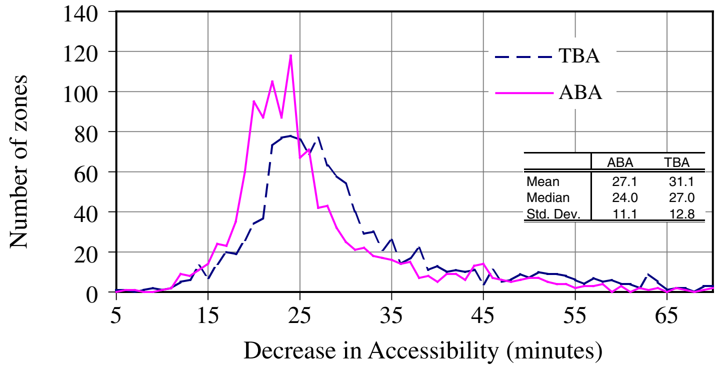

Fig. 6. Distributions of the activity-based accessibility (ABA) and trip-based accessibility (TBA) values.

work tour occurs, the ABA covers all activities and tours of the day and reflects the full array of adjustments that one can make in reacting to the peak-period toll. Some worker activity patterns include secondary tours that do not occur during the peak period, and that are therefore not negatively affected by the policy. Also, a worker could switch to travel to or from work in the off-peak, or could work from home, or could change work commute travel mode, or in the long term could change their home or work location. The ABA measure captures all these adjustments except the change in residential location. In contrast, the TBA measure can only reflect the change in mode or work location. The ABA measure's more realistic representation of scheduling flexibility results in lower estimates of accessibility impacts.

Fig. 7 shows the spatial distribution of accessibility impacts as calculated by the ABA and TBA, in a long-term analysis in which the work location is not fixed and the normalization expresses accessibility impact in equivalent minutes.[6] In these maps, each of the four darker shades corresponds to 10 min intervals of accessibility impacts, starting with the darkest shade relating to the smallest accessibility impact of 0–10 min, the second darkest shade representing 10–20 min impacts, and so on. Comparing the two maps, we can see that both measures indicate that the residential zones that receive the smallest loss of accessibility as a result of the peak-period toll are those at the center of the city. This is intuitive, because the CBD contains the highest density of activities (and therefore many can be accessed without driving) as well as the best transit service (and therefore there is a higher propensity to use and greater ease of switching to transit). Note that the 0–10 min region in the TBA is larger than in the ABA. This is likely because while the CBD provides many employment opportunities, it has a lower proportion of the opportunities for other household activities such as shopping, services, recreation, and social visits. Since the TBA measures accessibility only for the work trip, it ignores the accessibility impact for non-work purposes. As distance from the center increases, the TBA eventually averages more than 10 min because the workers need to get to work and fewer work opportunities are within 10 min. The 10 min threshold is hit sooner with the ABA because it includes the smaller (but still present) effect of the toll on non-work trips.

[6] Only accessibilities in minutes are displayed, because using dollars resulted in a similar plot.

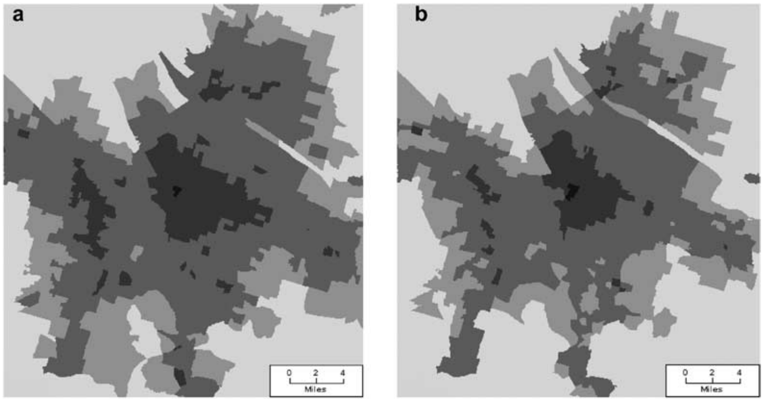

Fig. 7. Comparison of activity-based accessibility (ABA) and trip-based accessibility (TBA) plots of relative accessibility.

The second through fourth levels, which contain zones with average decreases in accessibility of 10–20, 20–30, and 30–40 min, respectively, are all larger for the ABA than for the TBA, reflecting the lower sensitivity to the policy of the ABA as discussed for Fig. 6.

5. Conclusions

This paper examines the properties and performance of the activity-based accessibility measure, which is generated from the day activity schedule model system. The novel aspect of the ABA is that it is a measure of accessibility to all activities in which an individual engages, incorporating both scheduling constraints and travel characteristics such as trip chaining. The ABA is a natural extension of the often used accessibility measure generated from a destination or destination-mode choice model. Like these more traditional utility-based measures of accessibility, the ABA can reflect taste heterogeneity, thereby reflecting the impact of socio-economic factors such as auto ownership, employment status, income, and household structure on accessibility. Aggregate measures such as isochrone or gravity, on the other hand, cannot reflect varying levels of accessibility based on socioeconomic factors. A second key advantage of the utility-based measures (both traditional and the ABA) is that they are able to reflect travel times and costs from all travel modes by including mode in the choice model from which the logsum is derived. This is an important feature in any accessibility measure as the true impact of, say, a transit oriented policy is dependent on the propensity and/or necessity with which one uses transit. Such a feature is substantially different from the isochrone or gravity models, which require either a single travel time as an input, or an ad-hoc generalized travel time that is not based on preferences. The final advantage of the ABA is that it encompasses activity-based travel choices throughout a whole day schedule, and thereby covers multiple choices for multiple trips conducted in different time periods of a day. This is substantially different from the traditional utility-based measure derived from a destination or mode-destination choice model, which can only model one particular trip purpose and cannot reflect scheduling or trip chaining.

Along with a mathematical presentation of the ABA and a presentation of the conceptual advantages of the new measure such as those listed above, the paper also presented empirical results from a case study in order to reflect the rich picture of accessibility made available by use of the ABA and to highlight differences between the ABA and more traditional measures of accessibility. The case study demonstrated many of the advantages presented in the above paragraph, including the following:

(1) The ABA is successful in capturing taste heterogeneity across individuals. This is shown in Fig. 3, where the peak period toll is shown to have a significantly larger impact on auto owners versus households that do not have a car. Such a result is expected, and the ABA provides quantitative evidence that is not available from aggregate measures. Fig. 6 provided another view of the importance of heterogeneity by showing how accessibility varies throughout an urban area based on socio-economic factors such as employment and auto ownership. Using a measure that recognizes such varying tastes and needs is important for any type of environmental justice study, because it will greatly impact the answer to who is impacted and by how much.
(2) The ABA combines different types of trips into a unified measure of accessibility, which is not possible with trip-based measures. Fig. 4 provides one valuable outcome of having a measure that reflects all activity types, which is that it makes it possible to generate direct comparisons of accessibility impacts from policy initiatives across such groups as employed and unemployed. Fig. 5d shows that while the work trip is an important part of overall accessibility, accessibility to other activities is important as well.
(3) The ABA reflects the impact of scheduling and trip chaining on accessibility (not possible with trip-based measures), which leads to a different picture of the magnitude (Fig. 6) and spatial aspects (Fig. 7) of accessibility impacts.

By taking into account all activities throughout the day as well as scheduling, trip chaining, and taste heterogeneity, the ABA improves our ability to quantify the "ease and convenience of access to spatially distributed opportunities". As such, it has the potential to provide new insight to the important questions of who is impacted and how by the imposition of various transportation and land use initiatives.

References

Ashiru, O., Polak, J.W., Noland, R.B., 2003. Development and application of an activity based space–time accessibility measure for individual activity schedules, Presented at the Annual Meeting of the European Regional Science Association, Jyvaskyla, Finland.

Ben-Akiva, M., Bowman, J.L., 1998. Integration of an activity-based model system and a residential location model. Urban Studies 35 (7), 1131–1153.

Ben-Akiva, M., Bowman, J.L., Gopinath, D., 1996. Travel demand model system for the information era. Transportation 23, 241–266.

Ben-Akiva, M., Lerman, S.R., 1977. Disaggregate travel and mobility choice models and measures of accessibility. In: Proceedings of the Third International Conference on Behavioral Travel Modeling, Tanenda, Australia.

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

Bowman, J.L., 1995. Activity based travel demand model system with daily activity schedules. M.S. Thesis at MIT.
Bowman, J.L., 1998. The day activity schedule approach to travel demand analysis. Ph.D. Thesis, MIT.
Bowman, J.L., Ben-Akiva, M., 2001. Activity-based disaggregate travel demand model system with activity schedules. Transportation Research A 35 (1), 1–28.
Bradley, M.A., Portland Metro, Bowman, J.L., Cambridge systematics, 1998. A system of activity-based models for Portland, Oregon. USDOT report number DOT-T-99-02, produced for the Travel Model Improvement Program of the USDOT and EPA, Washington, DC.
Burns, L.D., 1979. Transportation, temporal, and spatial components of accessibility. Lexington books. D.C. Health, Lexington, Massachusetts.
Chen, C., 1996. An Activity-Based Approach to Accessibility. Ph.D. Thesis, University of California, Irvine, USA.
Department of Environment, 1996. Policy and Procedure Guidelines, PPG 6.
Domencich, T., McFadden, D., 1975. Urban Travel Demand: A Behavioral Analysis. North-Holland, Amsterdam.
Geertman, S.C.M., van Eck, R., Jan, R., 1995. GIS and models of accessibility potential: an application in planning. International Journal of Geographical Information Systems 9 (1), 67–80.
Hägerstrand, T., 1970. What about people in regional science? Papers of the Regional Science Association 24, 7–21.
Handy, S.L., Niemeier, D.A., 1997. Measuring accessibility: an exploration of issues and alternatives. Environment and Planning A 29, 1175–1194.
Hanson, W.G., 1959. How accessibility shapes land-use. Journal of the American Institute of Planners 25, 73–76.
Huff, D.L., 1963. A probabilistic analysis of shopping center trade areas. Land Economics 39, 81–90.
Kwan, M., 1998. Space–time and integral measures of individual accessibility: a comparative analysis using a point-based framework. Geographical Analysis 30 (3), 191–216.
Kwan, M.-P., Murray, A.T., O'Kelly, M.E., Tiefelsdorf, M., 2003. Recent advances in accessibility research: representation, methodology and applications. Journal of Geographical Systems 5 (1), 129–138.
Lenntorp, B., 1976. Paths in space–time environments: a time-geographic study of movement possibilities of individuals. Lund Studies in Geography, Series B, Human Geography, vol. 44. The Royal University of Lund, Sweden.
McFadden, D., 1978. Modelling the choice of residential location. In: Karlquist, A. et al. (Eds.), Spatial Interaction Theory and Residential Location. North Holland, Amsterdam, pp. 75–96.
Miller, H.J., 1991. Modeling accessibility using space-time prism concepts within geographical information systems. International Journal of Geographical Information Systems 5, 287–301.
Neuburger, H., 1971. User benefit in the evaluation of transport and land use plans. Journal of Transport Economics and Policy 5, 52–75.
Pirie, G.H., 1979. Measuring accessibility: a review and proposal. Environment and Planning A 11, 299–312.
Recker, W.W., 1995. The household activity pattern: general formulation and solution. Transportation Research B 29 (1), 61–77.
Vickerman, R.W., 1974. Accessibility, attraction and potential: a review of some concepts and their use in determining mobility. Environment and Planning A 6, 675–691.
Wachs, M., Kumagai, T.G., 1973. Physical accessibility as a social indicator. Socioeconomic Planning Science 7, 327–456.