Operationalizing Time-Space Prism Accessibility in a Building-Level Residential Choice Model
Empirical Results from the Puget Sound Region

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ABSTRACT
The concept of accessibility has long been theorized as a principal determinant of household residential choice behavior. Research on this influence is extensive but the empirical results have been mixed. Further, the measurement of accessibility must contend with complications arising from the increasing prevalence of trip-chains, non-work activities, and multi-worker households, as well as reconcile person-specific travel needs with household residential decisions. This paper contributes to the literature by addressing the gap framed by these issues and presents a novel residential choice model with three main elements of innovation. First, it operationalized a time-space prism (TSP) accessibility measure, which the authors believe to be the first application of its kind in a residential choice model. Second, it represented the choice sets in a building-level framework, the lowest level of spatial disaggregation available for modeling residential choices. Third, it explicitly examined the influence of non-work accessibility at both the local- and personal-level. This residential choice model was applied in the Puget Sound Region using a 2006 household activity survey. The model estimation results confirmed that accessibility remain an important influence, with individual-specific work accessibility as the most critical consideration. By using the TSP approach, it was established that non-work accessibility in a trip-chaining context does contribute to the residential choice decision, even after accounting for work accessibility. Empirical tests also revealed a useful aggregation method to incorporate individual-specific accessibility measures into a household-level choice model.

INTRODUCTION
Generally defined as a measure of the ease of access between entities in different locations (1), the concept of accessibility reflects the possibilities for activities, such as employment and shopping, and has long been theorized as a principal determinant of household residential choice behavior. The classic monocentric city model in urban economics held central the trade-off relationship between commuting and land costs in explaining residential locations (2, 3).

Research on the influence of accessibility on residential choice is extensive but the empirical results have been mixed. Recent reviews of this body of literature have found, in general, accessibility to be a modestly positive explanatory variable (4, 5) but its influence on residential choice behavior is secondary to and confounded by other household, dwelling, and neighborhood characteristics (6, 7). Some studies observed the importance of both local and regional accessibility [e.g., Handy (8); Waddell and Nourzad (9)], while others concluded that accessibility has diminished significance in the predominately polycentric urban structures of contemporary cities [e.g., Giuliano and Small (10); Gordon and Richardson (11)].

The lack of significance for accessibility as explanatory variables in some residential choice models implies either there is no influence or that the data or methodologies used were not adequate. The latter interpretation warrants consideration as there remain important unresolved issues in measuring accessibility and examining it in a residential choice context. In spite of notable calls for more detailed measurements [e.g., Handy and Niemeier (12); Lee (13)] and disaggregate modeling approaches [e.g., McFadden (14, 15), most empirical studies of accessibility and residential choice remain limited to aggregate, typically home-location-based, accessibility measures and spatial representations at the Transportation Analysis Zone (TAZ) or higher level of geography. Further, many studies continue to rely solely on simplistic trip-based measures of accessibility in residential choice models despite the increasing prevalence of multi-purpose trips and trip-chaining behaviors (16, 17) and the advance of activity-based methods [e.g., Ben-Akiva and Bowman (18); Miller (19); Kwan (20)]. One of the questions plaguing this literature is whether there is a significant omitted variable bias: the accessibility of non-work activities within a time-bounded space. There is considerable accumulating evidence that households are increasingly comprised of multiple workers (21) and, therefore, cannot minimize the commute of one worker. Additionally, the fraction of trips attributed to non-work activities has been steadily increasing (21). The relevant question, then, is whether the increasing presence of multiple workplaces, coupled with the need to address non-work activities and related travel, are significant omitted variables in the residential location calculus. The authors seek to respond to this question by proposing a time-space prism approach to measure the influence of access to non-work discretionary activities during the return segment of the home-work tour.

To address the issues described above, this paper presents a novel residential choice model that incorporates both household-level place-based and disaggregate, individual-specific accessibility measures, while controlling for a wide range of household, dwelling, and neighborhood attributes. This model has three main elements of innovation. First, it includes the operationalization of a time-space prism (hereafter abbreviated as TSP) accessibility measure, which the authors believe to be the first application of its kind in a residential choice model. The TSP measure uses a theoretically and behaviorally meaningful activity-based approach that explicitly recognizes time-space constraints and considers multi-purpose trip-chains (19, 22). Second, the model choice sets are at the building-level, the lowest level of spatial disaggregation available for modeling residential choices.
MEASURES OF ACCESSIBILITY IN THE CONTEXT OF RESIDENTIAL CHOICE

The body of empirical research on accessibility and residential choice spans at least half a century (24). The accessibility measurement approaches used can be broadly classified into four categories: proximity-based, gravity-based, isochrone, and utility-based; each approach is described in turn below.

Proximity-Based Accessibility
Some of the simplest indicators of accessibility, thus relatively easy to calculate and understand, are proximity-based measures. This is an objective, place-based, approach that provides spatial information on the closeness of a residential location, in terms of travel time, distance, or generalized cost, to other activities (e.g., time to shopping center, distance to highway on-ramp, commuting cost to employment). The classic monocentric city model is based on proximity to the central business district (2, 3). In the job-housing balance literature, proximity-to-employment measures have been central to the assessment of urban spatial structures and the evaluation of land-use and transportation policies (25, 26). Some researchers have observed commuting cost to be influential on residential location [e.g., Weisbrod et al. (6); Levinson (26)] but others found it to have only a limited role in this choice [e.g., Giuliano and Small (10); Gordon and Richardson (11)].

Gravity-Based Accessibility
Formalized in the groundbreaking work on accessibility and residential land use by Hansen (24), the gravity-based approach is so called because the measures are derived from the denominator in the gravity model for trip distribution (12). This is a zonal approach that weights the potential of opportunities for interaction, quantified as the amount of an activity, by a deterrence function representing travel time, distance, or generalized cost. A generic formulation to calculate $A_i$, the accessibility for residents in zone $i$ is

$$A_i = \sum_j a_j f(c_{ij}),$$

where $a_j$ represents the quantity of opportunities in zone $j$ (e.g., the number of jobs or people) and $f(c_{ij})$ is a deterrence function for traveling from $i$ to $j$.

Gravity-based accessibility is also an objective measure where only the zonal-level of service is described. It provides a generalized measure of regional accessibility and has been extensively used with some success to measure access to employment and people (7, 8, 24, 27).

Isochrone Accessibility
A special case of the gravity-based measures is the isochrone approach, where the deterrence function in Equation 1, $f(c_{ij})$, is equal to one within a defined range of travel (e.g., within $x$ distance or travel time), and zero otherwise (28). Also known as the cumulative opportunities approach, these measures estimate accessibility only in terms of the quantity of opportunities available within arbitrary limits. Some success has been shown in using these measures to capture both local (9) and regional (23) accessibilities in residential choice models but the predictive powers, in general, are relatively small.

Utility-Based Accessibility
Grounded in travel demand modeling and Random Utility Maximization (RUM) theory, the utility-based approach is individual, or agent-based, as it explicitly considers behavior characteristics of the decision maker, be it modeled as a household or an individual (29). RUM theory assumes that an agent making a choice will select the alternative with the highest utility relative to all other available choices. The accessibility $A$ at location $i$ for agent $n$ can be

Analyses at this level allows for direct representations of dwelling qualities (e.g., types of building and tenure) and their interactions with household characteristics (e.g., disposable income defined as income less rent). Third, this is one of the few empirical studies in the literature to explicitly explore the influence of non-work accessibility in the residential choice. While research by Zondag and Pieters (5) and Srour et al. (23) found limited and negative accessibilities, respectively, to non-work opportunities for certain household types using broad, regional measures, this work examines local and personal non-work accessibilities. This paper contributes to the body of empirical research by illustrating the strong influence of accessibility on residential choice and demonstrating the powers of disaggregate measurement and modeling approaches in capturing accessibility impacts.

Following this introduction, sections detailing the relevant literature and the concept of the TSP accessibility measure are presented. They are then followed by an explanation of the residential choice model application in the Puget Sound Region, a description of the data used in the analysis, and a discussion of the model estimation results and their validations.
defined as
\[ A_{in} = \ln \left[ \sum_c \exp \left( V_{cn} \right) \right], \]  
where \( V_{cn} \) is a vector of observable attributes for choice \( c \) in a specified choice set \( C_n \) available to agent \( n \). This formulation is known as the logsum and is equivalent to the denominator of the commonly used multinomial logit (MNL) model (14).

In recent residential choice models, the use of logsum accessibility as composite indicators of regional accessibility has prevailed and the results generally show a modest influence (5, 9, 23). Despite the disaggregate nature of this approach, logsum values are commonly derived from trip-based travel demand models that can only consider broad categories of households. Further, there are pragmatic problems arising from the logsum calculations from many operational mode choice models producing theoretic values of the logsum that are positive and, therefore, at odds with the interpretation of travel as a disutility. In one approach to address some of these deficiencies, Ben-Akiva and Bowman (18) designed a residential choice model integrated with an activity-based model system. Accessibility was estimated at the household member-level as the maximum utility among the daily activity schedules available to each individual given a residential location. The empirical results from that residential choice model, however, did not provide a superior fit to the data compared to the trip-based model.

TIME-SPACE PRISM ACCESSIBILITY

To the best of the authors’ knowledge, a TSP approach for measuring accessibility in a residential choice model has not been previously examined in the literature. Moreover, little prior research has explicitly explored the role of accessibility to non-work activities in the residential location choice. The next two subsections first explain the fundamental concepts and then describe the operational procedures developed in this research.

Fundamental Concepts

Some fundamental concepts of the TSP relevant to the understanding of this paper are presented here. For a more comprehensive examination of this construct as accessibility measures, the readers are encouraged to explore seminal works by Miller (19) and Kwan (20).

Conceived in the time-geography framework by Hågerstrand (22), the TSP models the ability of individuals to access and participate in activities at different locations over time and provides a valuable tool to measure individual accessibility. It explicitly recognizes the basic temporal and spatial constraints within which human interactions take place and, therefore, offers a powerful perspective to analyze individual behaviors. As Hågerstrand (22) noted, time is a finite resource which must be used by individuals to travel and participate in spatially dispersed and temporally limited activities.

The TSP delimits the locations in time and space that can be physically reached by an individual during a given time interval. Figure 1 shows an example of a TSP in three-dimensional schematic form, with the x-y plane representing geographic space and the vertical axis denoting time. The bold solid line traces the movement of an individual in time-space, where a vertical segment parallel to the time-axis indicate no movement in space during that time interval (e.g., \( t_0-t_1, t_2-t_3 \)). A diagonal segment (e.g., \( t_1-t_2 \)) represents travel through geographic space over time; the slope (i.e., change in time over change in space) expresses the inverse of the velocity. The TSP itself, shown in bold dashed lines as the volume contained by the two oblique elliptical cones with a common base, does not trace observed movements through time-space. Rather, it defines the region of space possible for an individual to be in at specified times. The TSP is determined by the time budget of an individual, the extent and the level of service (i.e., travel velocities) of the transportation network, and temporal-spatial constraints such as the need to be at particular locations at particular times. In the example illustrated in Figure 1, an individual can leave the workplace, point \( W(x_2, y_2) \), at time \( t_1 \) and must return home, point \( H(x_1, y_1) \), at \( t_4 \), yielding a time budget equivalent to \( t_4 - t_1 \) for travel and activity participation. The projection of the three-dimensional TSP onto the two-dimensional geographic space delimits solely the spatial extent within which one can travel and is called the Potential Path Area (PPA). The PPA is shown in Figure 1 as the dotted elliptical shape on the x-y plane. Note that although lines are drawn straight and ellipses smooth in this schematic, the TSP and the PPA can be irregularly shaped depending on the availability and quality of the transportation system.
Operational Procedures

A wide variety of accessibility measures derived from the TSP has been proposed; a review of six major approaches that have been used in various simulation or empirical settings can be found in Kim and Kwan (30). The operational procedures used in this residential choice model application are based on the Feasible Opportunity Set (FOS) approach, which focuses on identifying potential opportunities constrained by the TSP. These procedures correspond closely, but with noted differences, to the operations of the prism-identification component of the Prism-Constrained Activity-Travel Simulator (PCATS) within the Florida Activity Mobility Simulator (FAMOS) system developed by Pendyala et al. (31). As in PCATS, this application used a TAZ system that comprises a region but the operational procedures described below can be adapted to lower levels of geography, even down to the discrete building-level.

First, the daily activity schedule of an individual, observed or simulated, is assessed to identify mandatory activities. These are commitments at predefined locations during predefined times (e.g., working hours at a workplace; t2-t3 at location W in Figure 1). These committed time intervals are called blocked periods and their complement is a set of open periods, when discretionary activities may take place (e.g., t3-t4 in Figure 1).

Second, given an open period and a travel mode, determine for each TAZ whether it can be visited with sufficient time remaining in order to participate in an activity. For example, a 30-minute minimum activity participation time may be subtracted from an individual’s time budget for grocery shopping after work; in Figure 1, the revised time budget = t4 – t3 – 30. This determination is repeated for all zones to identify the set of feasible TAZs for visit, providing a maximum spatial extent akin to the PPA.

Finally, the cumulative opportunities approach is applied to the set of feasible TAZs to quantify the amount of opportunities that are available to an individual in an open period given the temporal and spatial constraints. For example, the size of the opportunities for grocery shopping may be estimated by counting the total number of grocery stores or summing the total building area for that purpose. This is consistent with some prior research highlighting the uneven distribution of opportunities and the value that consumers place on the range of opportunities for activity engagement (20, 30).

By using the TSP framework, the impact of land-use and transportation system changes on activity-travel patterns would be evident in this accessibility measure. If the transportation network performance or the density of
opportunities decreases, then the set of feasible TAZs or the measure itself, respectively, decreases. Similarly, if travel is better or more opportunities exist, then increases are expected.

**PUGET SOUND REGION APPLICATION**

The TSP accessibility measure described above was operationalized in a residential choice model for the Seattle, Washington metropolitan area using a 2006 household activity survey. The modeling infrastructure employed was the residential choice component of the UrbanSim system of land-use and transportation models (32, 33). The following subsections describe the data, explain the model specifications, and present the estimation results.

**Data**

The Puget Sound Regional Council (PSRC) 2006 Household Activity Survey (34) was the primary source of data for modeling accessibility and residential choice behavior. This was complemented by 2005 building and parcel information from county tax assessment offices, 2000 business establishment files from the state unemployment insurance database, 2000 census data, 2006 travel model results from the PSRC, and other regional geo-spatial data representing environmental, political, and planning features.

Executed as a two-day activity and travel diary for all household members 16 years of age and older, the PSRC 2006 Household Activity Survey obtained valid data from 4,739 households, representing 10,516 persons. The survey has x-y coordinate residential location information for all households, which enabled assignment to individual buildings for modeling. The survey also contains data on the length of time in which each household has resided at the current residence and the location of the previous home. Thus, it is possible to identify movers who have recently made relocation decisions and establish the distance between the current and previous residences. A subset of 1,677 households who moved in the past 5 years before the survey was selected for use in the residential choice model to be temporaneously consistent with the other data.

All activity and travel records for each person in this survey were linked up as tours and the primary destination and purpose of each tour were identified. For the entire dataset, there are 27,306 person-tour records and more than one third of them (9,257) are home-based work tours, making it by far the most common tour type. Of these work tours, 50.1% had at least one stop other than at the workplace; 20.2% involved one or more stops on the way to work and a striking 41.9% contained at least one activity on the work-home return segment. In the latter case, the majority of the stops were made for shopping, eating out, or personal business (e.g., banking, dry-cleaning service). The prevalence of these multi-stop home-based work tours is consistent with national trends observed elsewhere (16, 17). The high frequency of stops for commercial activities made on the work-home return segment suggests that the after work open period, as shown in the example in Figure 1, may be an especially important accessibility consideration. It is, therefore, during this period when a TSP accessibility measure indicating the quantity of shopping, dining, and other consumer-type opportunities was applied for each worker.

Residential and workplace location data, as well as activity and travel schedules from the survey were used to help construct the after work TSP accessibility variable. A majority of the workplace data has x-y coordinates associated but this information is incomplete; the lowest level of geography common to all records is the TAZ. Thus, the spatial constraints of the TSP measure were modeled at the workplace and home TAZs. The temporal constraints, on the other hand, were modeled on the joint distributions of the observed workplace departure and home arrival times for all tours that included at least one stop in the open period after work. A set of these times that define the temporal dimension of the TSP is randomly assigned to each worker and a 30-minute minimum activity time is incorporated into the time budget calculations.

Other socio-demographical information in the survey data that is relevant to the residential choice model includes household income and size; the age and work/school status of each member; and the nature of the residential tenure (i.e., rent or own).

**Model Structure and Specifications**

The Puget Sound Region application of UrbanSim was recently applied at the building- and parcel-level and is among the most disaggregate metropolitan-scale modeling systems currently in operation. Model estimation at this level of detail can have significant improvements over more aggregate specifications and this is likely due to the closer match between the modeled entities and behaviors and those observed in the real world (33).

The Household Location Choice Model (HLCM) component of UrbanSim uses a standard discrete choice modeling framework. The configuration of the HLCM used in this research is the familiar MNL structure (14, 29) of the form

$$R_i(c) = \frac{\exp(V_{cn})}{\sum_c \exp(V_{cn})},$$

(3)
where $P_n(c)$ is the probability that household $n$ chooses alternative $c$ in an available choice set $C_n$. The attractiveness of $c$ for $n$ is expressed by the utility function,

$$V_{cn} = \alpha X_c + \beta H_n X_c,$$

where $X_c$ is an array of characteristics describing alternative $c$, $H_n$ is an array of attributes for household $n$, and $\alpha$ and $\beta$ are parameter arrays to be estimated. This utility expression highlights the underlying logic that when considering a residential choice decision, households take account of their own characteristics (e.g., household income and size, lifecycle stage) as well as those of the available housing options (e.g., unit size, neighborhood compositions, accessibility to work and other activities). Note that the interaction term $H_n X_c$ allows household attributes to enter the choice model with the housing characteristics as they cannot be specified by themselves; there would be no variations in them among the alternatives and no way to estimate coefficients for such variables.

The unit of analysis for the choice set used in this paper is the individual residential building and the modeled choice behavior is that of the household. Ultimately, housing units are the elemental basis for residential choice but the most detailed and complete datasets available are for buildings and parcels. Since almost 91% of the 986,157 residential buildings in the 2005 housing stock inventory for the Puget Sound Region are of the single-family residential (SFR) type, which depicts individual housing units, there are vast overlaps between the building and housing-unit representations. Further, building-level analysis represents the alternatives being considered much more realistically than those at higher geographies as it is possible to define the residential choice explicitly as a bundled choice for a particular physical building and a location on which it is situated. Gridcells, TAZs, neighborhoods, or other aggregate spatial units can only describe important qualities such as building type (e.g., SFR or apartments), tenure, price, and size imprecisely as proportions or multi-building averages.

The number of alternatives in the universal choice set is considered to be the same as the total number of residential buildings and is too large for model estimation. A random sampling of alternatives from the full universe, which has been shown to yield parameter estimates without a loss of consistency (14, 29), was employed. In this case, each residential building is weighted equally for sampling and the choice set consisted of one chosen alternative and twenty-nine randomly sampled non-chosen ones.

The explanatory variables specified in this residential choice application were selected from a wide assortment of measures for their theoretical and statistical significances; Table 1 summarizes them and provides brief descriptions. The theoretical meanings are explained here and the statistics are presented in the next section. The first variable, residential_units, accounts for the higher relative probability of finding housing in a multi-unit building, compensating for the equal weights assigned to each building in the random sampling of alternatives. The next two variables, same_area_type and same_area, are dummies designed to capture the relationship between a current residence and a previous one. Other residential choice research has shown that household moves are mainly a local process (5) and the 2006 household activity survey data revealed that approximately 50% of movers are 4 miles (6.4 km) or less from their previous residence, and 75% are 9 miles (14.4 km) or less. The Kitsap dummy variable tries to capture the special characteristics of Kitsap County, which is physically separated from the other three counties in the region by the Puget Sound. The population_density variable is expected to account for a general preference for lower residential density, all else being equal, as suggested by urban economic theory (2,3) and substantiated by empirical evidence (4, 9).
TABLE 1 Residential Choice Model Explanatory Variables and Descriptions

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>residential_units</td>
<td>Log of number of residential units in building</td>
</tr>
<tr>
<td>same_area_type</td>
<td>Dummy of building in same area type as previous household (HH) location</td>
</tr>
<tr>
<td>same_area</td>
<td>Dummy of building in same area as previous HH location</td>
</tr>
<tr>
<td>Kitsap</td>
<td>Dummy of building in Kitsap County</td>
</tr>
<tr>
<td>population_density</td>
<td>Log of zonal population density</td>
</tr>
<tr>
<td>high_inc × size</td>
<td>Dummy of high HH income (inc) × log of average dwelling size (sq ft/unit)</td>
</tr>
<tr>
<td>mid_inc × size</td>
<td>Dummy of mid HH inc × log of average dwelling size (sq ft/unit)</td>
</tr>
<tr>
<td>low_inc × size</td>
<td>Dummy of low HH inc × log of average dwelling size (sq ft/unit)</td>
</tr>
<tr>
<td>disposable_inc</td>
<td>Log of HH inc less average dwelling price per unit</td>
</tr>
<tr>
<td>inc × condo</td>
<td>Log of HH inc × dummy of condo residential building</td>
</tr>
<tr>
<td>inc × MFR</td>
<td>Log of HH inc × dummy of multi-family residential (MFR) building</td>
</tr>
<tr>
<td>one_pers × not_SFR</td>
<td>Dummy of one-person HH × dummy of not SFR building</td>
</tr>
<tr>
<td>renter × MFR</td>
<td>Dummy of renter HH × dummy of MFR building</td>
</tr>
<tr>
<td>kids × SFR</td>
<td>Dummy of HH with children × dummy of single-family residential (SFR) building</td>
</tr>
<tr>
<td>kids × kids_HH</td>
<td>Dummy of HH with children × percent HH with children within 600m</td>
</tr>
<tr>
<td>young × young_HH</td>
<td>Dummy of young HH (average adult age ≤ 30) × percent young HH within 600m</td>
</tr>
</tbody>
</table>

### Accessibility

- **work_logsum**: Zonal average logsum, weighted by proportions of zone-to-zone trips, for AM home-based-work (HBW) drive alone trips.
- **neigh_shops**: Log of number of shopping type jobs (retail, food, & other services) within 600m.
- **work_travel_time**: Individual worker travel time for AM HBW drive alone trips to workplace location (maximum value between up to 2 workers).
- **TSP_shops**: Log of number of shopping type jobs (retail, food, & other services) in time-space prism for the work-to-home leg of the HBW tour (maximum value between up to 2 workers).

The next six variables are a set of household income interactions with different building characteristics. Income is a powerful indicator of a household’s expected ability to afford and preference for different types of housing. The first three interact categories of household income with housing unit size and it is expected that the households in the highest income group would be better able to compensate for the higher prices and utilities of larger homes, relative to those in the other income groups. The disposable_inc variable compares the household income to an annual imputed rent and describes the amount of resources remaining for other consumption needs after paying for housing. The remaining two interactions are intended to capture the preferences for condo and multi-family residential (MFR) types of buildings, relative to SFR, among households with different incomes.

The remaining control variables are interactions that include household composition characteristics. The first two describe the preferences of one-person and renter households, respectively, for multi-unit buildings. The next two express the desires of households with children for neighborhoods with SFR buildings and other children, respectively. The final variable indicates the clustering of young people.

The last four variables listed in Table 1 are accessibility measures designed to capture the quality of access to different opportunities, at the local- and regional-level and in between. The work_logsum variable is a utility-based generalized measure of regional accessibility for employment. The neigh_shops variable uses a cumulative opportunities approach to estimate the availability of shopping-type activities in the immediate vicinity of a residential location. Both of these are objective, place-based accessibility measures while the other two are individual-specific. The work_travel_time variable computes the home-to-work network travel time by the drive alone mode, for each worker with a fixed non-home workplace, relative to each residential choice. Similarly, the TSP_shops variable operationalizes the TSP accessibility measure concept with a focus on the work-to-home segment for each worker and shopping opportunities. Since both of these measures are at the individual-level while the residential choice is modeled at the household-level, various methods of aggregation including sums and averages were examined. It was revealed by empirical tests that choosing the maximum value among the workers in multi-worker households can best fit the data.
**Estimation Results**

A series of residential choice models were estimated to demonstrate the influence of the different accessibility measures and the results are shown in Table 2. Model 1 is a base model specified only with the control variables. The subsequent models, from 2 through 5, progress from one to the next with the specification of one additional accessibility measure.

**TABLE 2 Residential Choice Model Results**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
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<td>0.692 17.4</td>
<td>0.629 16.1</td>
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<td>same_area</td>
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<td>2.66 26.4</td>
<td>2.80 27.0</td>
<td>2.34 23.3</td>
<td>2.53 24.3</td>
</tr>
<tr>
<td>Kitsap</td>
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<td>0.866 8.50</td>
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<td>1.73 14.4</td>
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<td>-0.101 -2.90</td>
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<td>-0.247 -6.77</td>
</tr>
<tr>
<td>high_inc × size</td>
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<td>0.952 11.3</td>
<td>1.01 11.9</td>
<td>0.816 9.67</td>
<td>0.892 10.5</td>
</tr>
<tr>
<td>mid_inc × size</td>
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<td>-0.333 -8.24</td>
<td>-0.304 -7.55</td>
<td>-0.313 -7.86</td>
<td>-0.311 -7.30</td>
</tr>
<tr>
<td>low_inc × size</td>
<td>-0.306 -5.37</td>
<td>-0.335 -6.46</td>
<td>-0.320 -5.50</td>
<td>-0.291 -4.67</td>
<td>-0.330 -5.49</td>
</tr>
<tr>
<td>disposable_inc</td>
<td>0.0631 3.20</td>
<td>0.0492 2.44</td>
<td>0.0657 3.23</td>
<td>0.0672 3.16</td>
<td>0.0714 3.31</td>
</tr>
<tr>
<td>inc × condo</td>
<td>0.0539 3.11</td>
<td>0.0405 2.17</td>
<td>0.0479 2.52</td>
<td>0.0524 2.81</td>
<td>0.0591 3.25</td>
</tr>
<tr>
<td>inc × MFR</td>
<td>-0.117 -6.27</td>
<td>-0.126 -6.54</td>
<td>-0.127 -6.52</td>
<td>-0.136 -6.90</td>
<td>-0.134 -6.91</td>
</tr>
<tr>
<td>one_pers × not_SFR</td>
<td>0.688 4.33</td>
<td>0.575 3.40</td>
<td>0.581 3.46</td>
<td>0.773 4.70</td>
<td>0.740 4.37</td>
</tr>
<tr>
<td>renter × MFR</td>
<td>2.85 14.6</td>
<td>2.90 14.5</td>
<td>3.05 15.0</td>
<td>2.84 14.0</td>
<td>3.00 14.7</td>
</tr>
<tr>
<td>kids × SFR</td>
<td>0.565 2.80</td>
<td>0.647 3.21</td>
<td>0.743 3.53</td>
<td>0.518 2.46</td>
<td>0.610 2.93</td>
</tr>
<tr>
<td>kids × kids_HH</td>
<td>0.0139 2.85</td>
<td>0.0120 2.45</td>
<td>0.0186 3.73</td>
<td>0.0262 5.13</td>
<td>0.0212 4.20</td>
</tr>
<tr>
<td>young × young_HH</td>
<td>0.0211 5.18</td>
<td>0.0247 5.55</td>
<td>0.0206 4.82</td>
<td>0.0220 4.98</td>
<td>0.0235 5.38</td>
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<tr>
<td>work_logsum</td>
<td>- -</td>
<td>0.635 3.06</td>
<td>0.573 2.88</td>
<td>0.711 3.61</td>
<td>0.808 3.84</td>
</tr>
<tr>
<td>neigh_shops</td>
<td>- -</td>
<td>- -</td>
<td>0.0715 3.88</td>
<td>0.0566 3.05</td>
<td>0.0507 2.70</td>
</tr>
<tr>
<td>work_travel_time</td>
<td>- -</td>
<td>- -</td>
<td>- -</td>
<td>-0.0248 -21.1</td>
<td>-0.0227 -17.6</td>
</tr>
<tr>
<td>TSP_shops</td>
<td>- -</td>
<td>- -</td>
<td>- -</td>
<td>- -</td>
<td>0.0473 3.37</td>
</tr>
<tr>
<td>Observations (N)</td>
<td>1677</td>
<td>1677</td>
<td>1677</td>
<td>1677</td>
<td>1677</td>
</tr>
<tr>
<td>Log-Likelihood (LL)</td>
<td>-3954.9</td>
<td>-3934.0</td>
<td>-3898.2</td>
<td>-3697.5</td>
<td>-3642.0</td>
</tr>
<tr>
<td>Null LL</td>
<td>-5703.8</td>
<td>-5703.8</td>
<td>-5703.8</td>
<td>-5703.8</td>
<td>-5703.8</td>
</tr>
<tr>
<td>LL ratio (ρ)</td>
<td>0.30662</td>
<td>0.31028</td>
<td>0.31657</td>
<td>0.35174</td>
<td>0.36147</td>
</tr>
<tr>
<td>Adjusted ρ (ρ')</td>
<td>0.30381</td>
<td>0.30730</td>
<td>0.31341</td>
<td>0.34841</td>
<td>0.35797</td>
</tr>
<tr>
<td>χ² likelihood ratio test</td>
<td>Reference</td>
<td>Reject (1) at &gt;0.999</td>
<td>Reject (2) at &gt;0.999</td>
<td>Reject (3) at &gt;0.999</td>
<td>Reject (4) at &gt;0.999</td>
</tr>
<tr>
<td></td>
<td>model only</td>
<td>significance</td>
<td>significance</td>
<td>significance</td>
<td>significance</td>
</tr>
</tbody>
</table>

Note: Dash indicate data not applicable

Each model in Table 2, except for the first, was compared to the preceding one using the chi-square likelihood ratio test. Each reference model was considered a restricted version of the next model that is being compared, with the omitted accessibility variable set to zero. This test evaluates the hypothesis that the restriction is
valid and has the form
\[ \chi^2[-2(LL_R - LL_U)] = \text{significance level for hypothesis rejection}, \]
where \( \chi^2 \) is the chi-square distribution function, and \( LL_R \) and \( LL_U \) are, respectively, the log-likelihood values of the restricted (reference) and unrestricted models. As shown in Table 2, this hypothesis is repeatedly rejected for all model pairs and these results suggest that the addition of each accessibility variable captured something that the preceding one did not.

The reminder of this section focuses on Model 5, the final one with the inclusion of the TSP accessibility measure. All estimated coefficients in this model have the expected signs and are statistically significant. Since it is not possible to directly compare the coefficient of one variable with that of another, a series of utility calculations were performed to help reveal the relative influence of each variable on residential choice. For each variable, two utilities, as expressed in Equation 4, were calculated using the estimated coefficients in Model 5. One utility is determined using the 5th percentile value of that variable and the other the 95th percentile; all other variables are held constant at the median values. The difference in utilities between the 5th and 95th percentile values is an indicator of the influence of that variable; the results for all variables are graphed in Figure 2.

![Figure 2: Difference in utilities between the 5th and 95th percentile values of each variable](image)

**FIGURE 2** Difference in utilities between the 5th and 95th percentile values of each variable

The set of interaction variables between household income and housing unit size had some of the largest differences in utilities, with the high income category variable taking the lead, and they have, therefore, the greatest influence on residential choice. This is consistent with expectations that high income households tend to derive relatively more utilities from larger homes, which are typically situated in attractive neighborhoods with other large homes. It is also confirmed by findings in the literature that dwelling-specific characteristics tend to dominate over accessibility variables (6, 7).

The second most influential variable shown in Figure 2 is work_travel_time and this clearly confirms the importance of work-related accessibility and the influential role of accessibility, in general, on residential choice. The next most influential accessibility measure is TSP_shops, which highlights the value of access to non-work activities and lends support to the omitted variable argument made in the introduction. Together, these two individual-specific variables show the usefulness of disaggregate accessibility measures. In particular, the TSP
approach was able to capture aspects of accessibility, trip-chaining and non-work activities, for which they were unaccounted in previous empirical studies.

CONCLUSIONS

The results of this research confirm that accessibility remain an important influence on residential choice. The measurement of this effect, however, must contend with complications arising from the increasing prevalence of trip-chains, non-work activities, and multi-worker households, as well as reconcile person-specific travel needs with household residential decisions. This paper contributes to the literature by addressing the gap framed by these issues and presents a novel residential choice model that is highly disaggregate in multiple dimensions.

As demonstrated in the model estimation results and the utilities calculations, individual-specific work accessibility is an extremely critical consideration in residential choice, even after controlling for various household, dwelling, and neighborhood characteristics. In the activity survey used for this research, approximately one-third of the person-tours recorded had work as the primary purpose and destination. Even though non-work tours are in the majority, it appears that work activities and, specifically, the ability to access them from the home location can influence residential choice more profoundly than access to anything else.

Given the prominence of non-work activities, however, it is difficult to imagine that access to them do not matter at all. By using a time-space prism approach to measure the amount of shopping-type opportunities available to each worker in a household on the work-to-home tour segment, it was established that non-work accessibility, after accounting for work accessibility, does contribute to the residential choice decision. Previous research has established relationships between non-work activities with travel behaviors and urban form [e.g., Handy (8)] but this work is one of the first to explicitly and positively link it to residential choice.

For both of these individual-specific measures, the household aggregation method with the best fit to the data was found to be choosing the maximum value among the workers in multi-worker households. This method was empirically tested to perform better than summation or averaging techniques and the results suggest that households prefer to minimize travel costs for work and optimize opportunities for non-work activities across all workers.

The ability of these and other measures in the residential choice model presented to capture the influence of accessibility was undoubtedly advanced by the highly detailed modeling framework. The building-level analysis of residential choice allows for the specification of building-specific attributes, provides more realistic representations of the residential choices and behaviors, and can provide substantial improvements to model estimation results over more aggregate models (33). Along with the time-space prism approach for measuring accessibility, the building-level residential choice model helps move operational planning models towards integrating land use models with activity-based travel models.

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REFERENCES


