WELFARE MEASURES TO REFLECT HOME LOCATION OPTIONS WHEN TRANSPORTATION SYSTEMS ARE MODIFIED

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ABSTRACT

Transportation system improvements do not provide simply travel time savings, for a fixed trip table; they affect trip destinations, modes, and times of day - and, ultimately, home and business location choices. This paper examines the welfare (or willingness-to-pay) impacts of system changes by bringing residential location choice into a three-layer nested logit model to more holistically anticipate the regional welfare impacts of various system shifts. Here, home value is a function of home price, size, and accessibility; and accessibility is a function of travel times and costs, vis-à-vis all destination options. The model is applied to a sample of 60 Austin, Texas zones to estimate home buyers' welfare impacts across various scenarios, with different transit fares, automobile operating costs, travel times, and home prices.

Results suggest that new locators' choice probabilities for rural and suburban zones are more sensitive to changing regional access, while urban and central business zone choice probabilities are more impacted by home price shifts. Automobile costs play a more important role in residential location choices in these simulations than those of transit, as expected in a typical U.S. setting (where automobile travel dominates). When generalized costs of automobile travel are simulated to rise 20%, 40%, and 60% (throughout the region), estimated welfare impacts (using normalized differences in logit logsum measures) for the typical new home buying household (with $70,000 in annual income and 2.4 household members) are estimated to be quite negative, at -$56,000, -$99,000, and -$132,000, respectively. In contrast, when auto's generalized costs *fall* everywhere (by 20%, 40%, and then 60%), welfare impacts are very positive (+$74,000, $172,500, and $320,000, respectively). Such findings are meaningful for policymakers, planners, and others when anticipating the economic impacts of evolving transportation systems, in the face of new investments, rising travel demands, distance-based tolls, self-driving vehicles and other changes.

Key Words: logsum differences, home location choice, welfare estimation, nested logit models, accessibility

INTRODUCTION

An understanding and consideration of residential location choice is fundamental to behavioral models of land use, and, ultimately, travel demand (Bina et al., 2006) and community welfare. Residential location choice decisions are influenced by a host of quantifiable and unquantifiable factors (e.g., Rossi, 2005), including home attributes (like home price, size, and age), travel costs (or/and travel times) and access (to freeways and transit stations, schools, jobs, parks and shopping centers), and household demographics (like income and the presence of children) (Habib and Kockelman, 2008). While challenging in execution, home (and business) location models are very valuable to the regional, long-run transportation planning process and to land use-transport policymaking (see, e.g., Ommere et al., 1999; Pinto, 2002; Hollingworth and Miller, 1996; Zhou and Kockelman, 2011).

The location choice model presented here relies on the method of logsum differences under a three-layer nested logit (NL) structure (for location, destination, and mode choice), with systematic utility modeled as a combination of home price, home size, and neighborhood accessibility. By making assumptions about home price, access attributes, travel cost and travel time sensitivity, and all model parameters, one can compute choice probabilities for each alternative setting and estimate welfare changes across scenarios (from equivalent variation or willingness-to-pay values), as experienced by households looking to locate in a region. While property valuation research has long examined the price impacts of local travel system changes (see, e.g., Mohring [1961], Allen [1981], Nelson [1982], Bajic [1983], Voith [1991], tenSiethoff and Kockelman [2002]), the approach pursed here takes the question of transportation improvements' welfare impacts to a whole new level, using direct measures of welfare economics across multiple and often competing costs shifts (using differences in logsums [Ben-Akiva and Lerman 1985], normalized to reflect dollar values, much like a willingness-to-pay metric).

Accessibility has long been theorized and proven a major determinant of residential location choice behavior (see, e.g., Alonso [1964], Zondag and Pieters [2006], and Lee and Waddell [2010]), and some existing literature helps to illustrate its influence on home location choice. However, a more detailed analysis still needed to explore the relationships among travel cost (or/and travel time), accessibilities, and home-buyer benefits. Moreover, the influence of each factor on house buyer benefits and the sensitivity of these benefits with changes in input variables merit examination. This work offers such a closer look, which should be of interest to policy-makers and planners when seeking methods for more rigorous and defensible methods of evaluating project and policy impacts.

BACKGROUND

Home location choice has been modeled in a variety of ways. Many rely on stand-alone choice models (e.g., NL, multinomial logit [MNL], and mixed logit specifications) for individual households, in isolation or as part of a larger land use model. For regional-scale modeling, many past models have kept track of household (and job) count totals at the zonal (aggregate) level. For example, Ben-Akiva and Bowman (1998) developed an integrated nested logit model for

Bostonians' residential location choices, along with members' activity and travel schedules. They found that the NL structure did not fit the data quite as well as a work-trip-based comparison model. Lee and Waddell (2010) devised a two-layer NL model (decision to move or to stay, followed by location choice) and confirmed the model's applicability with a case study in Seattle, Washington. Zhou and Kockelman (2011) explored a series of models for household and firm location choice around Austin, Texas, and found that that a three-layer NL structure, with location choice nested within home type choice, provided reasonable estimates. MNL models have also been popular. For example, Zhou and Kockelman (2008) used such models to simulate location choices for three different household types, using data on recent home buyers survey in Austin, Texas. The found that working households evaluate commute time differently when choosing their home location, with higher home-price-to-income ratios having a strong negative impact on their choice probabilities.

Other papers have examined residential location choice within a larger, land use framework. Dang et al. (2011) established a household residential location choice model for a mono-centric city to quantitatively explore the evolution of urban residential housing consumption based on data from a survey in Beijing, China. Findings indicate that the balance between commuting costs and housing costs has become the key variable in the residential location selection process, similar to findings from Yang (2006) and Kockelman (2008). Zhang and Kockelman (2013) developed a spatial general equilibrium model to explore the endogenous relations between urban sprawl, job decentralization, and traffic congestion, and compared the efficiency and welfare impacts of anti-congestion policies. Results indicate that firms tend to decentralize while households move toward the city center as congestion grows.

To describe the relationship between land-use and residential location choice, many researchers have used an accessibility index (AI) as a parameter. Srour et al. (2002) used different accessibility indices to estimate residential location choice and noted that job accessibility affect residential land values positively in statistically and economically significant ways, with distance to the central business district (CBD) and household head's workplace location playing important roles in residential location predictions. Zondag and Pieters (2006) built a move-stay choice model and a residential location choice model by home type (with data from The Netherlands), and showed that the role of accessibility is significant but small compared with the effect of demographic factors, neighborhood amenities, and dwelling attributes. Lee et al. (2010) proposed a time-space prism (TSP) accessibility measure, and applied it to residential location choice in the Central Puget Sound region. The study confirmed that accessibility is an important factor in residential location choice, with individual-specific work accessibility being the most critical consideration. Bina et al. (2006, 2009) ranked the importance of housing and location attributes (home price, commute time to work, perception of crime rate, attractive neighborhood appearance, commute time to school, and access to major freeways are the top six) by using linear regression models which utilized an accessibility index calibrated from logsums from travel demand models of home-based work trips.

The rule-of-half (RoH) and logsum differences are two typical methods in transport economics to estimate welfare. In the case of modeling home location choice, RoH method cannot be used for the home buyer/mover benefits calculation since there is no added demand (with just one home per household, typically). However, RUM assumptions are suitable for developing a location choice model, and the logsum differences can be used to determine home buyer/mover welfare under the assumption that each household chooses its home location to maximize its utility function involving all parameters considered. McFadden (1978, 1981) used logsum differences based on RUM assumptions (with Gumbel-type error terms) to estimate user benefits and losses when their travel (or others' travel) context changes. Many applications using logsums as an evaluation measure have been conducted in Europe, USA and other countries for policy (decision) making, land use modeling, and road (congestion) toll demand prediction (see, e.g., Jong et al., 2005; EXPEDITE Consortium, 2002; Odeck et al., 2003, Castiglione et al., 2003; Kalmanje and Kockelman, 2004). Logsum differences have also been used to evaluate land-use strategies in a climate change context. Geurs et al. (2010) evaluated data from The Netherland and showed that logsum accessibility benefits from land-use policy strategies can be quite large compared to investment programs for road and public transport infrastructure, largely due to changes in trip production and destination utility, which are not measured in the standard rule-of-half benefit measure.

While much research has been conducted on home location choice analysis, previous studies typically focus on what and how the factors affect the home buyer's/mover's decision. Additionally, the majority of home location choice studies are specific cities, districts or zones based on SP (Stated Preference) or RP (Revealed Preference) datasets, under the assumption that people choose the home that enables them to achieve the largest utilities. The change in house buyer's utilities and benefits needs to be examined more deeply in a welfare context. Adding to the previous research on location choice, this paper presents a three-layer NL model with destination-mode choice nested in location choice, using logsum differences to estimate household welfare.

METHODOLOGY

As discussed above, home location choices are regularly represent a trade-off between housing type (including variables of home price, size and age) and site accessibility, with income, household size, presence of children, job locations, and other socio-economic factors also playing roles (see, e.g., Zondag and Pieters, 2006; Dang et al., 2011; Zhou and Kockelman, 2007, 2008, 2011; Habib and Kockelman, 2008). Based on random-utility theory, logit-type models (McFadden 1978) have been widely used to explore this important household choice. The MNL framework has been the most common approach (e.g., Tu and Goldfinch, 1996; Hunt et al., 1994; Sermons and Koppelman, 2001; Zhou and Kockelman, 2008), with the assumption that all unobserved factors (among competing home alternatives) are uncorrelated and homogeneous. NL models have also been applied here, often to predict both home location and home size (Habib and Kockelman, 2008; Zondag and Pieters, 2006; Brian and Waddell, 2010) or activity-based accessibility (Ben-Akiva and Bowman, 1998).

This study relies on both MNL and NL equations, with systematic utility values that combine home price, home size and logsum accessibility metrics to specify (and then simulate) location choice behaviors. The study then uses normalized logsum differences to quantify the welfare effects of transportation system changes, along with other model variations. These methods, model structure, and applications are described below.

Model Structure for Location Choice

In evaluating home location choice, it is useful to first determine the most important aspects and attributes of that choice, such as home price, number of bedrooms, number of living areas, home age, lot size, travel time to work and recreation, and so on. This paper uses home price, home size, and logsum-based accessibility metric (for the home neighborhood) as the critical choice attributes (consistent with recent research[1]), and employs an MNL specification to estimate the probability of choosing each location. A common practice in classifying household location is to use census tracts, zip codes, or traffic analysis zones (TAZs) (McFadden, 1981; Habib and Kockelman, 2008; Bina and Kockelman, 2009) as the location choice set. This model assumes the region of study is divided into *L* location zones, with each zone serving as a location alternative, and as a potential trip destination for the logsums that characterize the origin zone's accessibility. Since home-location access is based on a two-level logsum (for destination and mode choices), the home-choice model specification becomes a 3-layer nested-logit model structure, as illustrated in Figure 1.

There are three distinct choice dimensions being modeled here, so the structure reflects three embedded nests. This NL specification allows clusters of similar options to exhibit correlated error terms (Ben-Akiva and Lerman 1985). From top to bottom are location choice, destination choice and finally, mode choice. The top level is the MNL home location zone model, where the probability of each household choosing to reside in a zone is computed as a function of home price, home size, accessibility and other variables. The middle level is a destination choice model (for any single trip) where people choose a destination for their typical trip to other zones (including origin zone) based on the logsums of mode choices (lowest level). Lastly, the lowest level of the NL structure is a mode choice model (for the trip between zones) by destination that accounts for the generalized cost (travel cost and travel time) of each mode (only auto and public transit [bus] are considered here). Reasonable behavioral parameter values were selected to characterize preferences. Figure 1 also shows the associated scale parameters (the μ values).

Logsum Method for User Benefits Estimation

As discussed in the literature review, use of logsum differences is a relatively recent approach for anticipating consumer surplus changes, than the more traditional rule-of-half method. It also comes with much more of a disaggregate perspective on choice dynamics, and requires the presence of competing choice alternatives (versus a single demand market, for example, as is common in more traditional rule-of-half applications). Logsum differences have been used for welfare analyses of land use and environmental policies, and in home location choice studies (e.g., USDOT, 2004; Geurs et al., 2010; Lee et al., 2010). When using a logit model with RUM assumptions (along with linear-in-income utility assumptions), consumer surplus changes are calculated as the difference between the expected consumer surplus levels $E(CS_n)$ before and after the change (i.e., across scenarios), reflecting all alternatives, as follows:

$$\Delta E(CS_n) = (1/\alpha_n)[\ln(\sum_i e^{V_{ni}^1}) - \ln(\sum_i e^{V_{ni}^0})], \forall n, i \qquad (1)$$

where superscript 0 and 1 refer to before and after the change, α_n represents the marginal utility of income for person *n* (can also be expressed as dU_n/dY_n, where Y_n is the income of person *n*), U_n is the overall utility for person *n*, V_n is the representative utility (indirect utility) for person *n*,

[1] Bina and Kockelman (2006, 2009) explored the mean rank of importance of housing and location attributes from two mover segments: home buyers and apartment renters. They found that home price (or apartment rent), travel time (to work), and access to major freeways are the most important attributes for home buyers and apartment buyers - among almost 20 attributes. Home size (including number of bedrooms and lot size) is also top-ranked by most home buyers.

and i denotes the choice alternatives available to person n. Thus, U_{ni} is the overall utility for person n choosing alternative i, and V_{ni} denotes the systematic or representative utility for person n choosing alternative i.

In this model, determining the probabilities of a home buyer choosing each location alternative is a key step. These probabilities are estimated by evaluating the characteristics of each alternative in order to assess an indirect utility associated with the alternative. In a MNL model, this may be expressed using formula (2) and (3).

$$P_i = e^{V_i} / \sum_{i=1}^{K} e^{V_i} \tag{2}$$

$$V_i = \beta_1 \cdot X_{i1} + \beta_2 \cdot X_{i2} + \beta_3 \cdot X_{i3} + \cdots + \beta_n \cdot X_{in} \tag{3}$$

where P_i is the probability of a user/consumer choosing alternative i from alternative choice set K; V_i is the representative utility(indirect utility) of alternative i, which is usually a linear function of attributes X_i (as shown in equation 3); and β_i is utility coefficient for each attribute.

MODEL SPECIFICATION

Some assumptions and simplifications are made in this NL model structure. For the top level, the sole variables assumed here to affect the location choice are accessibility, home price and home size. In the second choice stage, the only variables affecting destination choice probabilities are the logsums for (auto and transit) mode options. At the bottom level, the only variables assumed to affect mode choices are travel time and travel cost (along with alternative specific constants, or ASCs, for each mode).

Based on the previous discussion of the NL model structure and calculation of logsum differences, key modeling equations (for generalized trip costs, systematic utilities, and inclusive values of the nested choices and choice probabilities) are as follows:

$$GC_{ldm} = VOTT \cdot TIME_{ldm} + COST_{ldm} \tag{4}$$

$$V_{ldm} = ASC_m - GC_{ldm} \tag{5}$$

$$\Gamma_{ld} = \frac{1}{\mu_1} \ln[\exp(\mu_1 \cdot V_{ld,transit}) + \exp(\mu_1 \cdot V_{ld,Auto})] \tag{6}$$

$$AI_l = \Gamma_l = \frac{1}{\mu_2} \ln[\exp(\mu_2 \cdot \Gamma_{l,\mathrm{d}_1}) + \exp(\mu_2 \cdot \Gamma_{l,\mathrm{d}_2}) + \ldots + \exp(\mu_2 \cdot \Gamma_{l,\mathrm{d}_n})] \tag{7}$$

Each trip's generalized cost (GC_{ldm}) is a linear function of travel time (*TIME*) and travel cost (*COST*) – which includes any tolls plus (other) operating costs -- between each (potential) home zone l (1:L) and each destination zone d, via mode m (for transit and auto), with all values of travel time (*VOTT*) assumed to be \$12/hr here. The systematic utilities (V_{ldm}) of these alternatives (shown in Eq 5 and 6) are measured in dollars, and include the appropriate mode's ASC (assumed to be 0 for the auto mode and -1.1 for transit, as used by Kockelman and Lemp [2011]). The expected utility of a destination zone, d, as shown in Eq. 6, lacks an attractiveness factor. Usually, destination zones differ in the number of work, shopping, recreation and other opportunities they offer (though TAZ boundary decisions often have a target population or population range in mind, so they are often roughly equivalent in terms of household trip generation). To avoid introducing land use effects, from variations in jobs (by type) or other attraction features, the models used here presume equal attractiveness, for household trip making, across all 60 zones, ceteris paribus. Travel times and costs vary, however, by mode and to each destination zone, given a starting (home) zone. So destination zones are not equally attractive, once travel costs are taken into account.

Equation 7's accessibility metric, AI_l, is the logsum, Γ_l, which denotes the inclusive value or expected maximum utility of the two-level (destination and mode) choices available to a home zone l. This term requires no normalizing coefficient, since the utilities, V, are already measured in dollars. Finally, at top level of the effectively three-level NL framework, the household's expected choice probability of each location is as follows:

$$\Pr_l = \frac{\exp(\mu_3.U_l)}{\sum_{l=1}^{L}\exp(\mu_3.U_l)} \quad (8)$$

$$U_l = \alpha_1 \cdot P_l + \alpha_2 \cdot SF_l + \alpha_3 \cdot AI_l \quad (9)$$

where Pr(.) represents the probability of a particular choice (home location choice); U denotes the expected maximum utility of the top level alternative; SF denotes the square footage (home size); and P denotes the home price. The α_1, α_2, and α_3 are indirect utility slope parameters on home price, home size and accessibility, which vary with each potential home zone l. In the following example, the values of α_1 and α_2 were calculated using Zhou and Kockelman's (2011) work[2], and α_3 was assumed to be the same AI coefficient (0.635) found in Lee and Waddell's (2010) paper, based on a logsum (for work trips) to all destination zones.

μ_1, μ_2, μ_3 serve as the scaling parameters parameters (which are the inverse of the inclusive value coefficients) for the mode, destination and location choices. Consistent with McFadden's random-utility theory, the scale parameters are usually assumed to fall from the lowest to the highest level nest (see, e.g., Kockelman and Lemp, 2011[3]). Here, scale parameters of 1.2 (μ_1) in the lowest, 1.1 (μ_2) in the middle nest, and 1.0 (μ_3) in the upper level nest were assumed. These are falling (from the lowest to the highest level nest), and the inverse of each lies between 0 and 1, consistent with RUM assumptions (Ben-Akiva and Lerman, 1985).

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[2] Zhou and Kockelman (2011) proposed a dwelling unit and location choice model for Austin's households based on a survey of Austin movers in 2005, and estimated coefficients on home Price-to-income ratio and SF-per-household-member variables to be -0.249 and +3.34. According to "City of Austin Community Inventory Report", from 2000 to 2007, the average median household annual income is between \$60,000 to \$70,000, household size is between 2.2 to 2.4 (and shows a declining trend). Thus, in this paper, an average household income \$70,000 and an average household size 2.4 are assumed (usually, the new home buyer households are wealthier and bigger-size than average households in Austin. In Bina and Kockelman (2009), the surveyed new home buyer's average income was \$93,256, and average household size was 2.27. Here, with the home price (P) and SF instead of home Price-to-income ratio and SF-per-household-member, the values of α_1 and α_2 can be estimated as $\alpha_1 = -0.249/7 = -0.0357$ and $\alpha_2 = 3.34/2.4 = 1.39$.

[3] Kockelman and Lemp (2011) relied on a 4-layer (destination, mode, time of day, and route) NL model, with scale parameters (μ_1, μ_2, μ_3, μ_4,) from the lowest-level nest to the highest-level nest assumed to be 1.8, 1.6, 1.4 and 1.2, to be consistent with random utility maximization theory (Ben-Akiva and Lerman 1985).

Estimates of consumer surplus changes (ΔCS) for each scenario (as compared to the starting or base case setting) were computed as well. Normalized logsums of systematic utilities are used here, as the basis for estimating those welfare changes, as follows:

$$\Delta \mathrm{C}S_n = \frac{1}{\alpha_n}\{\ln[\sum_l \exp(\mu_3 U_l^1)\text{-}\ln[\sum_l \exp(\mu_3 U_l^0)]\} \tag{10}$$

Here, CS can be measured between any two scenarios, but this paper looks primarily at the change in consumer surplus as measured in reference to the base scenario. Here, α_n represents the marginal utility of income for person *n,* assumed to be the reciprocal of α_1's absolute value, so all α_n are set to \$10,000/0.0357 = \$280,110.

NUMERICAL EXAMPLES

In order to fully appreciate the changes of consumer surplus changes (home buyer welfare effects) as a result of the changes in access, home price and other factors, the NL model was applied to a variety of scenarios, which vary, for example, the generalized costs of either mode, auto's operating cost and travel time, home prices, and VOTT. The travel time and cost data used in this example come from TAZ-based skim files of Austin, Texas' Capital Area Metropolitan Planning Organization (CAMPO) for a 3-county network in year 2000. 60 of the original 1,074 TAZs were strategically selected as a representative sample of the larger region's location alternatives.

Table 1 shows the types and distribution of these 60 zones, which reflect 4 types of land use: rural, suburban, urban, and central business district (CBD) zones (according to CAMPO definitions). Here, CBD zones are assumed to have the highest home prices and rural zones the lowest, thanks to land-rent increases typical of more central/accessible locations. For simplicity, the home prices are assumed to be \$200,000, \$300,000, \$600,000 and \$1,000,000 in the rural, suburban, urban and CBD zones. Similarly, home sizes are assumed to fall with increased density, with 3,000 ft^2, 2,500 ft^2, 2,000 ft^2 and 1,500 ft^2 serving as the interior/built space for rural, suburban, urban and CBD homes. Accessibility metrics are much harder to guess at, and were estimated as logsums using actual travel times and travel costs between the 60 zones (travel costs referred to here as "fares", for the transit alternative, and reflecting tolls and vehicle operating costs in the case of the automobile mode[4]). Table 2 shows the main variables and parameters used in the example, and Table 3 shows the base scenario for the 60 zones.

Under this base scenario, probabilities of location choices are calculated via Equation 8, with the rural and suburban zones' share being larger due to their relatively higher utilities. The shares of residents in the four types of zones are 0.480, 0.400, 0.117 and 0.0026 (for rural, suburban, urban, and CBD in that order). The model also shows that the probability of a household choosing a rural or suburban zone increases greatly with higher AIs. For example, rural zone 4 and suburban zone 37 have relatively high AIs (0.906 and 1.902) within their zone type, and the probabilities of these two zones being chosen (0.0499 and 0.0328) are relatively large; but for urban zones, especially the CBD zones, even zones with very high AIs are unlikely to be chosen (e.g., zone 60 has the highest accessibility 2.934, but the probability of a household choosing this zone is very

[4] According to AAA (2013), the average cost of driving a medium sedan 15,000 miles a year was \$0.61 per mile, in 2013. Here, a value of \$0.60 per mile is used to estimate the COST_{ldm} value shown in Equation 4.

small). This indicates that the relative desirability of rural and suburban zones is more sensitive to AIs. In other words, network changes that improve or worsen the accessibility of rural and suburban zones have great impacts on households' decisions to locate in these zones, while the choice to locate in urban and CBD zones is less sensitive to such accessibility changes.

Several other scenarios are also explored to understand effects on home buyer welfare levels. Scenario 1 examines the effect of transit's generalized travel costs by increasing and decreasing GC_{ij} values by 20, 40 and 60 percent. Scenario 2 examines travel time cost effects, while Scenarios 3 and 4 further explore changes in the auto mode, by varying its operations costs and travel times, respectively. Finally, Scenario 5 examines the impact of changing home prices on home buyers' benefits.

Figure 2 shows the corresponding changes in AIs and the changing probabilities with the changes in inputs in these scenarios. Table 4 shows the shares of households selecting each of the 4 zone types under different scenarios. Finally, Table 5 compares the home buyer welfare across scenarios. It shows how the generalized cost of automobile travel and home prices play key roles in home buyer welfare gains and losses.

When varying the generalized costs of transit, there are almost no changes or very slight changes in each location's AI and probability of being chosen. For example, when all GC_{ij} values are increased 40%, total probabilities of location choices in CBD and urban zones have no change on average, while those in rural and suburban zones only rose an average of 0.0001 and -0.0001. Home buyer welfare change, as estimated using the logsum difference between the Base scenario and Scenario 1, is very small. When all GC_{ij} values are increased 20%, 40%, and 60%, the estimated average-mover welfare changes are computed to be -\$30.8, -\$42.6, and -\$47.7. However, when all GC_{ij} values are decreased 20%, 40%, and 60%, the corresponding welfare gains are estimated to be \$101, \$592, and \$4,870. The model implies that decreasing transit fares impact home buyer benefits more significantly than increasing fares.

Changes in generalized costs of auto affect home locations' AI and probability more significantly, as can be seen in Figure 2(a). Larger spacing between the AI lines implies that AI is quite sensitive to auto's generalized cost. When all GC_{ij} values are increased by 40%, average location choice probabilities in the rural and CBD zones rise by 0.0210 and 0.0002, while those in suburban and urban zones drop an average of 0.0197 and 0.0015. This may appear inconsistent with intuition: one typically expects higher generalized auto costs to make more central housing locations relatively more accessible and thus relatively more desirable. However, from Equations (4), (5), (8) and (9), one can find that as GC_{ij} increases, the AI of each zone decreases, making AI differences between zones smaller, so this shift toward less accessible zones can result.

Welfare gains and losses (ΔCS) estimated via logsum differences in the base scenario and scenario 2 are quite large: when all GC_{ij} values are increased 20%, 40%, and 60%, the estimated user welfare losses are -\$55,946, -\$98,858, and -\$13,2160. When all GC_{ij} values fall 20%, 40%, and 60%, the estimated welfare gains are \$74,127, \$172,506, and \$319,787. As in the case of transit, such results imply that reductions in automobile travel costs impact home buyer welfare more significantly than the same percentage increase in auto travel costs. The above welfare gains and losses are calculated for home buyers with a \$70,000 annual income and 2.4 person household size. For home buyers with \$45,000 annual income and 4-person household size, the estimated user welfare changes are -\$36,299, -\$64,083, and -\$85,581 when all GC_{ij} values are increased 20%, 40%, and 60%; they are \$48,151, \$113,699, and \$207,662 when all GC_{ij} values fall by 20%, 40%, and 60%. A \$15 per hour VOTT was also tested, resulting in higher accessibility indices (than with the \$12-per-hour VOTT used above), but estimated house buyer benefits were smaller than before.

Scenarios 3 and 4 are the detailed analyses of changes in operation cost and travel time inputs of the auto mode. Figures 2(b) and 2(c) describe the AIs and probabilities of each location being chosen under these scenarios. As seen in these figures, line shapes are very similar to those in Figure 2(a), but the spacing between lines is smaller, implying that AI and the probability of a location being chosen are less sensitive to changes in vehicle operation costs and travel times than to changes in overall generalized costs. In Scenario 3, for example, when all operation cost values are increased 40%, the total probabilities of location choices in rural and CBD zones rise by 0.0149 and 0.0001, on average, while those in suburban and urban zones drop an average of 0.0134 and 0.0016; when all operation cost values are decreased 40%, the total probabilities in suburban zones rises by 0.0109, while those in rural, urban, and CBD zones drop an average of 0.0086, 0.0020, and 0.0003. As discussed previously, AIs of rural and suburban zones are more sensitive to the road networks changes. Scenario 4 offers almost the same trend as shown in Scenario 3.In comparing results of Scenarios 3 and 4, one can see how lower vehicle operations costs may provide more benefits to a new home buyers than reduced travel time, when they are changed by the same proportion or precentage. For example, the estimated welfare effect is \$99,940 when all operating costs fall 40%, versus \$51,546 when all travel times fall 40%. Table 5 shows these numbers in detail.

Scenario 5 explores the effect of home price on people's home location choice and welfare. As displayed in Figure 3, the shares of location choice in suburban zones are less sensitive to the home price shifts (as compared to all other zone types). For example, zones 10, 37, 48 and 60 fall in rural, suburban, urban, and CBD locations, respectively. When all home price values increase 40%, the shares of these four representative zones shift by 0.0037, -0.0010, -0.0085 and -0.0008. The corresponding estimated welfare losses are -\$56,678, -\$111,383, and -\$164,438 when all home prices increase 20%, 40%, and 60%, and welfare gains are \$59,036, \$120,885, and \$186,079 when home price fall 20%, 40%, and 60. When one changes VOTT from \$12 to \$15 per hour, the benefits one observes following house price reductions (in Table 5) are smaller than before, while losses from house price increases are somewhat greater than before. It seems home buyer benefits are impacted slightly more when home prices fall than when they rise by the same amount (in dollars or percentage terms).

CONCLUSIONS

An understanding of residential location choice provides a foundation to explore the relationship between land use and transportation, which leads to more accurate travel demand models. Previous research on household location choice usually focus on the factors affecting the household buyer's location choice decision, with accessibility generally accepted as a principal determinant of residential location selection. In this paper, a three-layer NL structure on house location choice is proposed and logsum differences are used to estimate the home buyer welfare changes as a result of various transportation and housing input changes. The systematic utility of a residence is considered as a function of home price, home size and home location zone's accessibility. This paper develops several scenarios to examine how transportation and housing price factors affect house location choice behavior and home buyer welfare.

Home buyer welfare estimated via logsum differences are very small due to the change of generalized cost of transit, AIs; and location choice probabilities of each location almost remain the same values when varing all the GC_{ij} values. The auto mode's costs are more important for most people's home location choice than is transit, people consider the AI based on automobile's access a lot when they make a location choice decision; Decreasing the values of travel costs or travel times have a more significant impact on home buyer welfare than increasing that; The higher the AIs, the larger the probabilities in most rural and suburban zones, it is also implied that in urban and CBD areas, home buyers usually pay more attention on home price or home size; The impact of home price on home buyer welfare is apparent compared to other attributes when they changing at the same speed/amplitude, and home buyer benefit mores when home prices fall by the same amount in dollars or percentage terms.

Of course, the analysis pursued here illustrates only a limited number of idealized scenarios under a nested logit model structure. Many other investigative opportunities and scenario extensions are feasible, which may highlight other key factors for regional welfare analysis following changes in the transportation and/or land use systems. For example, one could examine the effects of changes in zone attractiveness, model parameters, and various other inputs, simultaneously or independently. User heterogeneity is also important to explore in more depth, since every household differs (in its demographic attributes, income, housing preference function, and values of travel time, for example). Moreover, uncertainty exists in all zones (and for all model parameters, as well as the model specification itself), with spatial autocorrelation in missing variables; and there are significant information-limitation issues for many movers (especially those new to a region), when evaluating a region's many location options. Thus, this topic area remains ripe for future investigation.

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REFERENCES

AAA (2013) Your Driving Costs: How Much Are You Really Paying to Drive? AAA Association Communication, Heathrow, FL. Available at http://newsroom.aaa.com/wp-content/uploads/2013/04/YourDrivingCosts2013.pdf.

Allen, G. (1981) Highway Noise, Noise Mitigation, and Residential Property Values. *Transportation Research Record* 812: 21-27.

Alonso, W. (1964) *Location and Land Use: Toward a General Theory of Land Rent*. Cambridge, MA: Harvard University Press.

Bajic, V. (1983) The Effects of a New Subway Line on Housing Prices in Metropolitan Toronto. *Urban Studies* 20: 147-158.

Ben-Akiva, M., Lerman, S. (1985) *Discrete Choice Analysis: Theory and Application to Travel Demand*. MIT Press.

Ben-Akiva M., Bowman J.L. (1998). Integration of an Activity-based Model System and a Residential Location Model. *Urban Studies* 35: 1131-1153.

Bina M., Kockelman K.M. (2009). Location Choice vis-à-vis Transportation: The Case of Recent Homebuyers. *The Expanding Sphere of Travel Behaviour Research* 18: 597-619.

Bina M., Warburg V., and Kockelman K.M. (2006). Location Choice vis-à-vis Transportation: The Case of Apartment Dwellers. *Transportation Research Record* 1977: 93-102.

Castiglione J., Freedman J., and Davidson W. (2003). Application of a tour-based microsimulation model to a major transit investment, San Francisco County Transportation Authority and PB Consult, San Francisco, California.

Dang Y., Zhang W., and Wu W. (2011). Residents Housing Preferences and Consuming Behaviors in a Transitional Economy: New Evidence from Beijing, China. *Progress in Geography* 30(10): 1203-1209.

Geurs K., Zondag B., Jong G. de, Bok M. de, (2010). Accessibility Appraisal of Land-Use / Transport Policy Strategies: More than just Adding up Travel-Time Savings. *Transportation Research* Part D: 382-393.

Gupta S., Kalmanje S., and Kockelman K.M. (2006). Road Pricing Simulations: Traffic, Land Use and Welfare Impacts for Austin, Texas. *Transportation Planning and Technology* 29(1): 1-23.

Hollingworth B.J. and Miller E.J. (1996). Retrospective Interviews and its application in study of residential mobility. *Transportation Research Record* 1551: 74-81.

Hunt J.D., McMillan J.D.P., and Abraham J.E. (1994). Stated preference investigation of influences on attractiveness of residential locations. *Transportation Research Record* 1466: 79–87.

Jong, G. de, Pieters M., Daly A., Graafland I., Kroes E., and Koopmans C. (2005). Using the Logsum as an Evaluation Measure: Literature and Case Study. Prepared for AVV Transport Research Centre. RAND Europe.

Kockelman K.M. and Lemp J.D. (2011). Anticipating new-highway impacts: opportunities for welfare analysis and credit-based congestion pricing. *Transportation Research* Part A 45 (8): 825-838.

Lee B.H.Y, Waddell P., Wang L. and Pendyala R.M. (2010). Reexamining the influence of work and nonwork accessibility on residential location choices with a micro analytic framework. *Environment and Planning A,* 42: 913 -930.

Lee B.H.Y. and Waddell P. (2010). Residential mobility and location choice: a nested logit model with sampling of alternatives. *Transportation* 37(4): 587-601.

McFadden, D. (1978). Modeling the choice of residential location. In Karlqvist, A.,Lundqvist, L., Snickars, F. and Weibull, J. (eds) *Spatial Interaction Theory and Residential Location*. North-Holland, Amsterdam.

McFadden, D. (1981). Econometric models of probabilistic choice. In Manski, C. and McFadden, D. (eds) *Structural Analysis of Discrete Data: With Econometric Applications*. The MIT Press, Cambridge, Massachusetts.

Meurs H. and Haaijer R. (2001). Spatial structure and mobility. *Transportation Research* Part D 6: 429-446.

Mohring, H. (1961) Land Values and the Measurement of Highway Benefits. *J of Political Economy* 49: 236-249.

Nelson, J. P. (1982) Highway noise and property values: A survey of recent evidence. *Journal of Transport Economics and Policy* 16(2): 117-38.

Nurul H., and Kockelman K. M. (2008). Modeling the Choice of Residential Location and Home Type: Recent Movers in Austin, Texas. Proceedings of the 87th Annual Meeting of the Transportation Research Board, Washington D.C.

Odeck J., Rekdal J., and Hamre T.N. (2003). The socio-economic benefits of moving from cordon toll to congestion pricing: The case of Oslo. Proceedings of the 82th Annual Meeting of the Transportation Research Board, Washington D.C.

Ommeren J.V., Roedveld P., and Nijkamp P. (1999). Job moving, residential moving and commuting: A search perspective. *Journal of Urban Economics* 46: 230-253.

Pinto S.M. (2002). Residential choice, mobility and the labour market. *Journal of Urban Economics* 51: 469-496.

Rossi P. (1955). *Why Families Move*. McMillan, New York.

Sermons, M.W. and Koppelman F.S. (2001). Representing the differences between female and male commute behavior in residential location choice models. *Journal of Transport Geography* 9 (2): 101–110.

Srour I.M., Kockelman K.M. and Dunn T.P. (2002). Accessibility Indices Connection to Residential Land Prices and Location Choices. *Transportation Research Record* 1805: 25-34.

tenSiethoff, B., and Kockelman, K. (2002) Property Values and Highway Expansions: An Investigation of Timing, Size, Location, and Use Effects. *Transportation Research Record* 1812: 191-20.

Tu Y. and Goldfinch J. (1996). A two-stage housing choice forecasting model. *Urban Studies* 33 (3): 517–537.

Voith, R. (1991) Transportation, Sorting, and Housing Values. *AREUEA Journal* 19 (2): 117-137.

Yang J. (2006). Transportation implications of land development in a transitional economy: Evidence from housing relocation in Beijing. *Transportation Research Record* 1954: 7-14.

Zhang W. and Kockelman K.M. (2013). Urban sprawl, job decentralization, and congestion: the welfare effects of congestion tolls and urban growth bounders. Proceedings of the 93rd Annual Meeting of the Transportation Research Board. http://www.ce.utexas.edu/prof/kockelman/public_html/trb14ugbsvstollingrents.pdf

Zhou B. and Kockelman K.M. (2008). Microsimulation of Residential Land Development and Household Location Choices: Bidding for Land in Austin, Texas. *Transportation Research Record* 2077: 106-112.

Zhou B. and Kockelman K.M. (2008). Neighborhood impacts on land use change: a multinomial logit model of spatial relationships. *Annals of Regional Science* 42(2): 321-340.

Zhou B. and Kockelman K.M. (2008). Self-selection in home choice: use of treatment effects in evaluating the relationship between the built environment and travel behavior. *Transportation Research Record* 2077: 54–61.

Zhou B. and Kockelman K.M. (2009). Predicting the Distribution of Households and Employment: A Seemingly Unrelated Regression Model with Two Spatial Processes. *Journal of Transport Geography* 17 (5): 369-376.

Zhou B. and Kockelman K.M. (2011). Land Use Change through Microsimulation of Market Dynamics: An Agent-based Model of Land Development and Locator Bidding. *Transportation Research Record* 2255: 125-136.

Zondag B. and Pieters M. (2006). Influence of Accessibility on Residential Location Choice. *Transportation Research Record* 1902: 63-70.

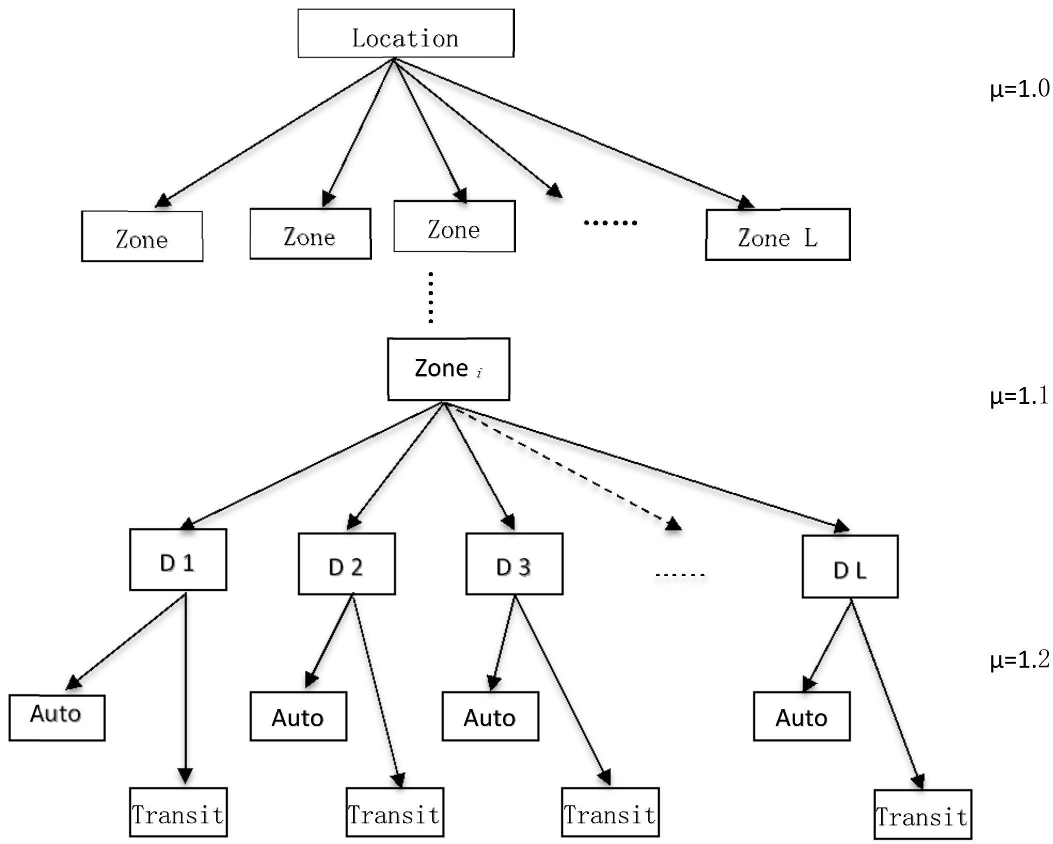


Figure 1 Nested logit model structure on home location choice

Table 1 Austin's TAZ sample

		Rural	**Suburban**	**Urban**	**CBD**	**Totals**
County	**Hays**	4	4	2	0	*10*
	Travis	9	15	12	2	*38*
	Williamson	4	5	3	0	*12*
Totals		*17*	*24*	*17*	*2*	*60*

Table 2 Variables and parameters used

Variable Used	Variable Description	Parameter Values	
Home price (P)	Average home price (10,000$)	α_1	-0.0357
Square footage (SF)	Average interior square footage (1,000ft2)	α_2	1.39
Accessibility (AI)	Logsums of mode-destination analysis based on travel time and travel cost	α_3	0.635
Scale parameter (μ)	Scale parameter for the lowest level	μ_1	1.2
	Scale parameter for the median level	μ_2	1.1
	Scale parameter for the highest level	μ_3	1.0
Alternative specific constants (ASC)	Alternative specific constants for Auto mode		0.0
	Alternative specific constants for Transit mode		-1.1
VOTT	Value of the travel time ($/h)		$12 per hr
Marginal utility of income (α_n)	Marginal utility of income for person *n*	α_n	$280,110

Table 3 Attributes for home location choice and probabilities in base scenario

Zone type	Zone ID	Home price ($10,000)	Home size (1,000ft^2)	AI	Proba bility	Zone type	Zone ID	Home price ($10,000)	Home size (1,000ft^2)	AI	Proba bility
1	1	20	3	-0.872	0.0161	2	31	30	2.5	1.230	0.0214
1	2	20	3	0.018	0.0284	2	32	30	2.5	0.995	0.0184
1	3	20	3	-0.098	0.0264	2	33	30	2.5	0.925	0.0176
1	4	20	3	0.906	0.0499	2	34	30	2.5	0.862	0.0169
1	5	20	3	-0.119	0.0260	2	35	30	2.5	1.431	0.0243
1	6	20	3	0.574	0.0404	2	36	30	2.5	0.836	0.0167
1	7	20	3	0.279	0.0335	2	37	30	2.5	1.902	0.0328
1	8	20	3	-0.195	0.0248	2	38	30	2.5	0.958	0.0180
1	9	20	3	0.040	0.0288	2	39	30	2.5	-0.092	0.0092
1	10	20	3	0.166	0.0312	2	40	30	2.5	-0.403	0.0076
1	11	20	3	0.263	0.0332	2	41	30	2.5	1.709	0.0290
1	12	20	3	-0.421	0.0215	3	42	60	2	1.363	0.0040
1	13	20	3	-0.850	0.0164	3	43	60	2	0.985	0.0031
1	14	20	3	0.777	0.0460	3	44	60	2	0.716	0.0026
1	15	20	3	-0.566	0.0196	3	45	60	2	1.237	0.0037
1	16	20	3	-0.628	0.0189	3	46	60	2	0.678	0.0026
1	17	20	3	-0.637	0.0187	3	47	60	2	1.215	0.0146
2	18	30	3	-0.891	0.0056	3	48	60	2	1.936	0.0230
2	19	30	2.5	0.807	0.0164	3	49	60	2	2.007	0.0060
2	20	30	2.5	0.191	0.0111	3	50	60	2	1.944	0.0058
2	21	30	2.5	0.570	0.0141	3	51	60	2	1.891	0.0056
2	22	30	2.5	0.863	0.0169	3	52	60	2	2.402	0.0077
2	23	30	2.5	0.623	0.0146	3	53	60	2	2.493	0.0082
2	24	30	2.5	0.883	0.0172	3	54	60	2	1.529	0.0044
2	25	30	2.5	0.593	0.0143	3	55	60	2	2.437	0.0079
2	26	30	2.5	0.105	0.0105	3	56	60	2	1.807	0.0053
2	27	30	2.5	1.583	0.0268	3	57	60	2	1.698	0.0049
2	28	30	2.5	0.928	0.0177	3	58	60	2	2.444	0.0079
2	29	30	2.5	0.548	0.0139	4	59	100	1.5	2.904	0.0013
2	30	30	2.5	-0.047	0.0095	4	60	100	1.5	2.934	0.0013
Total Probabilities		0.4799 (Zone type 1)		0.4004 (Zone type 2)		0.1171 (Zone type 3)		0.0026 (Zone type 4)			

Note: Zone type 1 = Rural zones (1-17), 2 = Suburban zones (18-41), 3 = Urban zones (42-58), 4 = CBD zones (59-60).

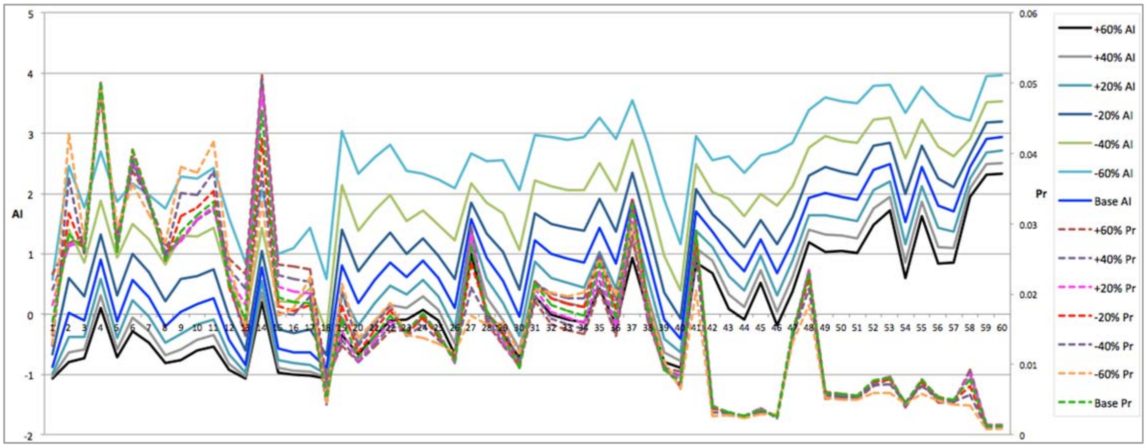
Table 4 Shares of home location for 4 types of zones due to variables changes

House price		60%	40%	20%	-20%	-40%	-60%
Transit GC	Rural	0.4800	0.4800	0.4800	0.4798	0.4792	0.4754
	Suburban	0.4003	0.4003	0.4003	0.4005	0.4009	0.4039
	Urban	0.1171	0.1171	0.1171	0.1172	0.1173	0.1181
	CBD	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026
Auto GC	Rural	0.5138	0.5009	0.4890	0.4764	0.4824	0.5038
	Suburban	0.3708	0.3807	0.3910	0.4070	0.4081	0.3987
	Urban	0.1125	0.1156	0.1173	0.1142	0.1076	0.0959
	CBD	0.0028	0.0028	0.0027	0.0023	0.0020	0.0016
Auto OC	Rural	0.5030	0.4948	0.4869	0.4744	0.4713	0.4720
	Suburban	0.3804	0.3870	0.3938	0.4064	0.4113	0.4140
	Urban	0.1138	0.1155	0.1167	0.1167	0.1151	0.1119
	CBD	0.0027	0.0027	0.0026	0.0024	0.0023	0.0021
Auto TT	Rural	0.4857	0.4829	0.4810	0.4801	0.4815	0.4844
	Suburban	0.3920	0.3952	0.3980	0.4020	0.4029	0.4029
	Urban	0.1196	0.1192	0.1184	0.1154	0.1132	0.1105
	CBD	0.0028	0.0027	0.0026	0.0025	0.0023	0.0022
Home price	Rural	0.5625	0.5368	0.5094	0.4484	0.4148	0.3791
	Suburban	0.3787	0.3882	0.3956	0.4017	0.3991	0.3918
	Urban	0.0583	0.0740	0.0934	0.1456	0.1792	0.2179
	CBD	0.0005	0.0009	0.0015	0.0042	0.0069	0.0112
Base scenario		Rural:0.4799; Suburban: 0.4004; Urban: 0.1171; CBD: 0.0026					

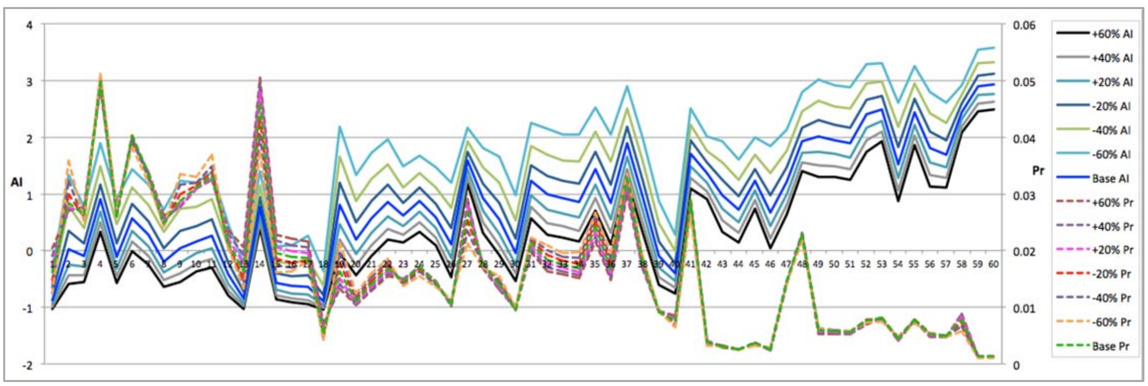
Table 5 Welfare effects of changing travel costs, times, and home prices (Income = $70,000, Household size = 2.4 persons, VOTT = $12/hr)

Scenarios \ Changes	**+60%**	**+40%**	**+20%**	**-20%**	**-40%**	**-60%**
Transit GC	-$47.7	-$42.6	-$30.8	$101.1	$591.5	$4,870
Auto GC	-$132,160	-$98,858	-$55,946	$74,127	$172,506	$319,787
Auto OC	-$94,290	-$68,089	-$37,063	$44,808	$99,940	$169,692
Auto TT	-$61,040	-$42,585	-$22,303	$24,537	$51,546	$81,299
Home Price	-$164,438	-$111,383	-$56,678	$59,036	$120,885	$18,6079
Auto GC[1]	-$80,661	-$60847	-$34,755	$46,993	$112,094	$206,804
Home Price[1]	-$174,640	-$124,185	-$72,106	$38,989	$99,511	$176,764

Note [1], the results are according to VOTT = $15/hr**.**



(a)



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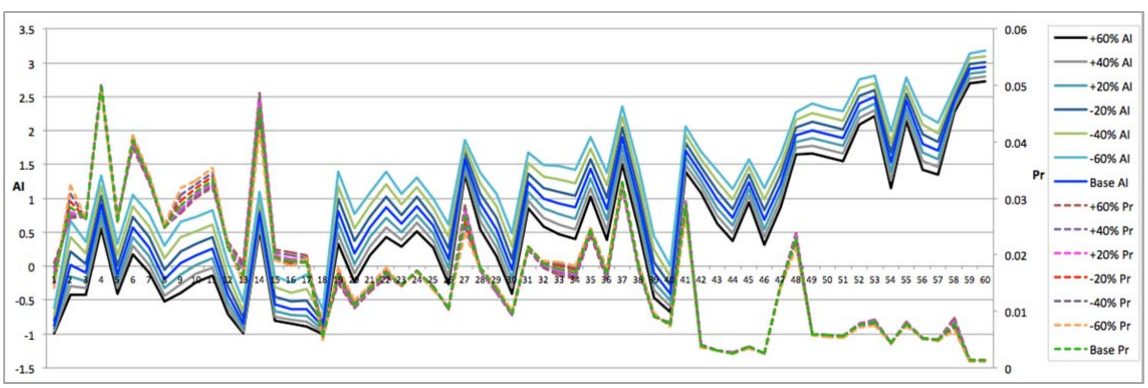

(c)

Figure 2 Changes in AI and zone choice probabilities following changes in auto's total (generalized) costs (a), in auto's operating costs (b), and in auto's travel times (c)

Note: X-axis denotes the 60 zones (potential home locations).

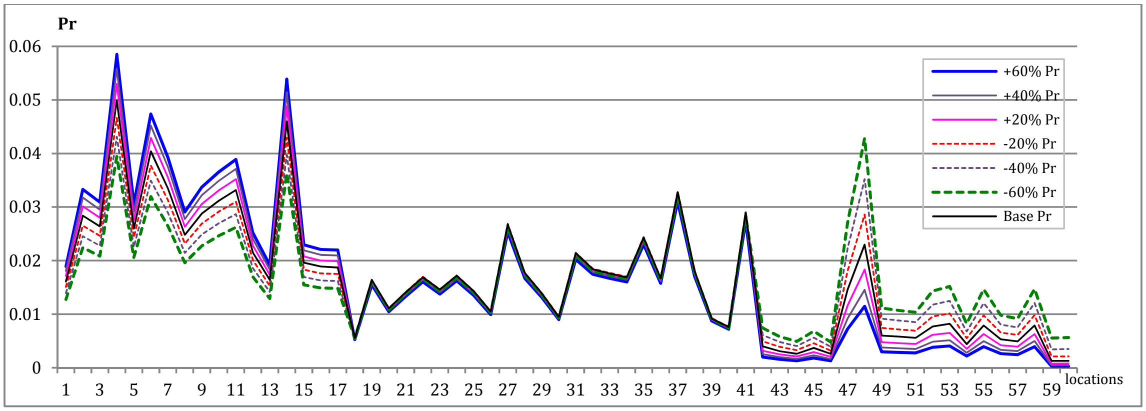

Figure 3   Changes in zone choice probabilities following home-price changes