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Author(s): Shuhong Ma and Kara M. Kockelman

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Welfare Measures to Reflect Home Location Options When Transportation Systems are Modified

by Shuhong Ma and Kara M. Kockelman

Transportation system improvements do not provide simply travel time savings, for a fixed trip table; they affect trip destinations, modes, 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 using logsum differences (which quantify changes in consumer surplus). 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 mode and 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.

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 1955), 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 (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 differences¹ 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 (Mohring 1961, Allen 1981, Nelson 1982, Bajic 1983, Voith 1991, TenSiethoff and Kockelman 2002), the approach pursued 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). The expected maximum utility of mode plus destination plus location and home choices depend on travel times and travel costs to all potential destinations. This approach is consistent with prior research, as cited in the paper (e.g., locators/movers pay much attention to work and school travel times, as well as access to major freeways and transit lines), but this paper's recognition of the location choice behavior is very novel.

Accessibility has long been theorized and proven a major determinant of residential location choice behavior (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 and nuanced analysis is needed to explore the relationships among travel costs and times, accessibilities, and home-buyer/residential locator 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 policymakers and planners when seeking methods for more rigorous and defensible methods of evaluating project and policy impacts. This work begins with a description of existing, related literature, followed by a description of methods and model specifications, regional examples, and key findings.

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 (2008a) used such models to simulate location choices for three different household types using survey data of recent home buyers in Austin, Texas. They 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 is key in the residential location selection process, similar to findings from Yang (2006) and Zhou and Kockelman (2008b). Zhang and Kockelman (2015) 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 affects 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, random-utility maximization (RUM) assumptions (where decision-makers are assumed to choose the alternatives that benefit them most) 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, the U.S., and other countries for policy (decision) making, land use modeling, and road (congestion) toll demand prediction (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 Netherlands and showed that such access benefits (with user benefits calculated using logsum difference following access changes) from land-use policy strategies can be quite large compared with 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

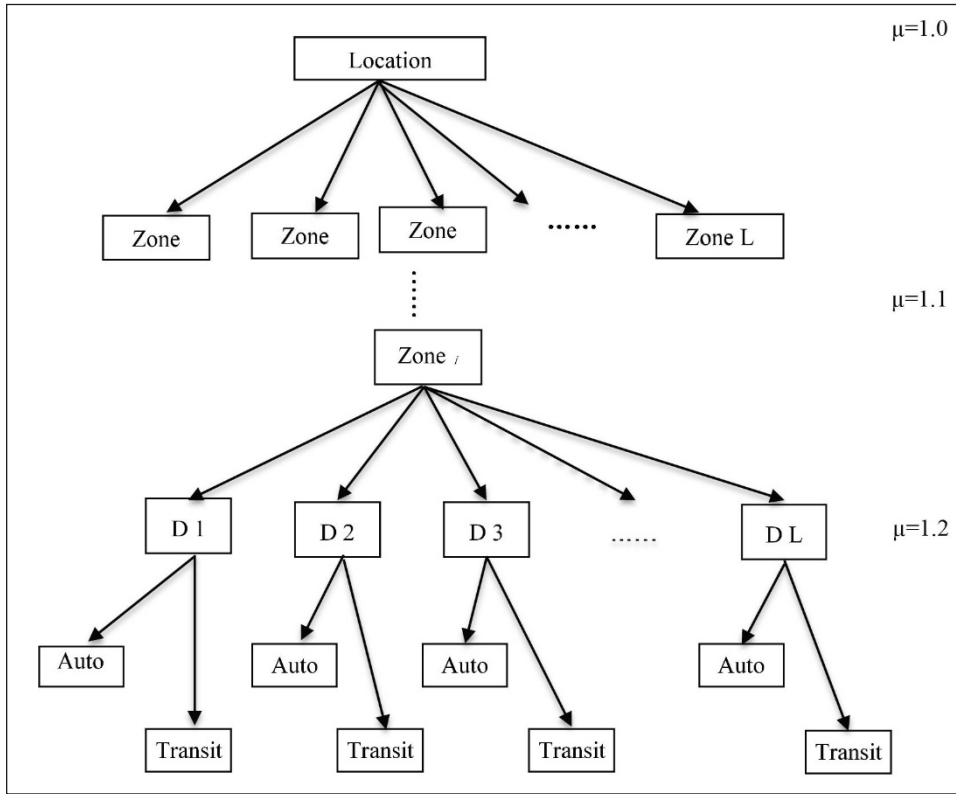
As discussed above, home location choices regularly represent a trade-off between housing type (including variables of home price, size, and age) and site accessibility, with income, household size, presence of children, job locations, and other demographic factors also playing roles (Zondag and Pieters 2006; Dang et al. 2011; Zhou and Kockelman 2008a, 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 (Tu and Goldfinch 1996; Hunt et al. 1994; Sermons and Koppelman 2001; Zhou and Kockelman 2008a, 2008c), 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; Lee 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 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 each home's price, size, and nested logsum-based accessibility metric (shown later, in Eq 7) as the critical choice attributes (consistent with recent research²), 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 three-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, as tested by Lemp and Kockelman (2008), were used here to characterize preferences. Figure 1 also shows the associated scale parameters (the μ values).

Figure 1: Nested Logit Model Structure on Home Location Choice

Logsum Method for User Benefits Estimation

As discussed in the literature review, use of logsum differences is a relatively more recent approach for anticipating consumer surplus changes than the more traditional rule-of-half method.³ 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 (USDOT 2004; Geurs et al. 2010; Lee et al. 2010). When using a logit model with RUM assumptions (i.e., that people anticipate and select the alternative that offers them maximum utility), 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:

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

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_{ni} is the representative utility (or indirect utility, often expressed as a function of travel time and cost) for person n to experience alternative i . 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 an MNL model, this may be expressed using Eqs (2) and (3).

$$(2) \quad P_i = e^{V_i} / \sum_{i=1}^K e^{V_i}$$

$$(3) \quad V_i = \beta_1 \cdot X_{i1} + \beta_2 \cdot X_{i2} + \beta_3 \cdot X_{i3} + \dots + \beta_n \cdot X_{in}$$

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 value parameters of the nested choices and choice probabilities) are as follows:

$$(4) \quad GC_{ldm} = VOTT \cdot TIME_{ldm} + COST_{ldm} \quad \text{Generalized costs}$$

$$(5) \quad V_{ldm} = ASC_m - GC_{ldm} \quad \text{Systematic utilities}$$

$$(6) \quad \Gamma_{ld} = \frac{1}{\mu_1} \ln[\exp(\mu_1 \cdot V_{ld,transit}) + \exp(\mu_1 \cdot V_{ld,Auto})] \quad \text{Expected max. utilities}$$

$$(7) \quad AI_l = \Gamma_l = \frac{1}{\mu_2} \ln[\exp(\mu_2 \cdot \Gamma_{l,d_1}) + \exp(\mu_2 \cdot \Gamma_{l,d_2}) + \dots + \exp(\mu_2 \cdot \Gamma_{l,d_n})] \quad \text{Accessibility indices}$$

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 (consistent with FHWA guidance [2015] and Lemp and Kockelman's [2011] simulations). 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:

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

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

where $\Pr(\cdot)$ 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,⁴ 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 three choice-levels' utility scaling parameters for the mode, destination, and location choices. These are the inverse of the logit model's inclusive value coefficients, as defined in Ben-Akiva and Lerman (1985), and they serve as coefficients in the utility expression. 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 2011⁵). 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).

Estimates of consumer surplus changes (ΔCS) for each scenario (as compared with 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:

$$(10) \quad \Delta CS_n = \frac{1}{\alpha_n} \{ \ln[\sum_l \exp(\mu_3 U_l^1)] - \ln[\sum_l \exp(\mu_3 U_l^0)] \}$$

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 $\$10,000/0.0357 = \$280,112$.

NUMERICAL EXAMPLES

In order to fully appreciate the 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 files⁶ of Austin, Texas' Capital Area Metropolitan Planning Organization (CAMPO) for a three-county network in the year 2000. Sixty (60) of the original 1,074 TAZs were strategically selected as a representative sample of the larger region's location alternatives. Therefore, the AI of one zone is an average access from its zone to the other 1,073 zones and can be calculated using Eq (7).

Table 1 shows the types and distribution of these 60 zones, which reflect four 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, due 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 (not far from Austin’s actual home prices.) Similarly, home sizes are assumed to fall with increased density, with 3,000 ft², 2,500 ft², 2,000 ft², and 1,500 ft² 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 automobile⁷). Table 2 shows the main variables and parameters used in the example, and Table 3 shows the base scenario for the 60 zones.

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

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 small [0.0013]). 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.

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 (1,000ft ²)	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

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%. 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 four 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 (as shown in Table 5). 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 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 (from Table 4: $0.5009-0.4800 = 0.0210$ and $0.0028-0.0026 = 0.0002$), while those in suburban and urban zones drop an average of 0.0197 and 0.0015 (from Table 4: $0.4004-0.3807 = 0.0197$ and $0.1171-0.1156 = 0.0015$). This may appear inconsistent with intuition: one typically expects higher generalized auto costs to make more central housing locations relatively more accessible and, therefore, relatively more desirable. However, from Equations (4), (5), (8), and (9), one notices how, as GC_{ij} increases, the AI of *each* zone decreases, making AI *differences* between zones smaller, so an overall shift toward less accessible zones can result.

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	Probability	Zone type	Zone ID	Home price (\$10,000)	Home size (1,000ft ²)	AI	Probability
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)			

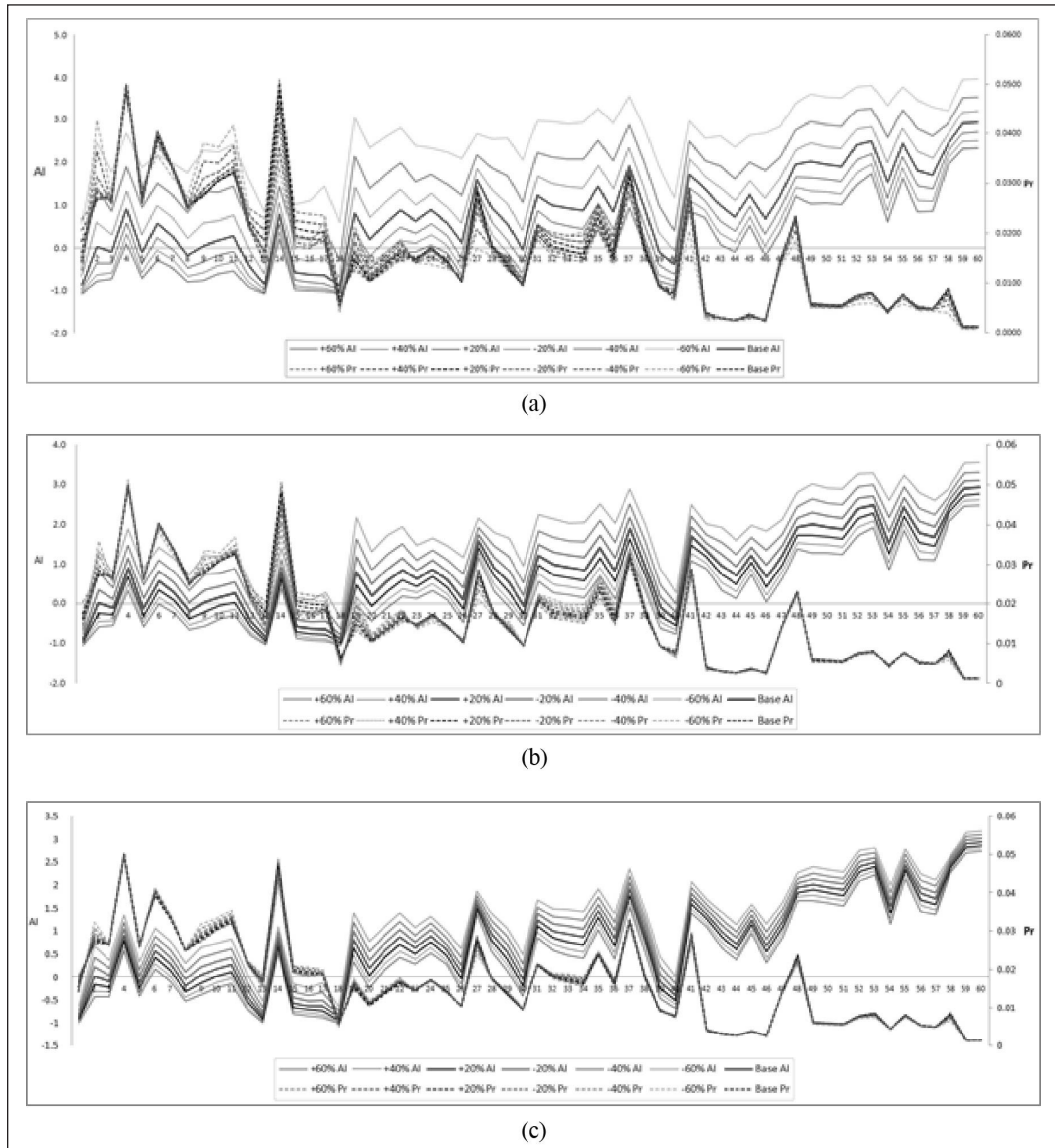
Note: Zone type 1 = Rural zones (1-17), 2 = Suburban zones (18-41), 3 = Urban zones (42-58), 4 = CBD zones (59-60).

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 -\$132,160, as shown in Table 5. 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 four-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 are smaller than before (i.e., as compared with those shown in Table 5).

Table 4: Shares of Home Location for Four Types of Zones Following Changes in Variables

		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					

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)

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 (from Table 4: $0.4948 - 0.4799 = 0.0149$ and $0.0027 - 0.0026 = 0.0001$), on average, while those in suburban and urban zones drop an average of 0.0134 and 0.0016 (from Table 4: $0.4004 - 0.387 = 0.0134$ and $0.1171 - 0.1155 = 0.0016$); when all operation cost values fall by 40%, the total probability of choosing a suburban zone rises by 0.0109 (from Table 4: $0.4113 - 0.4004 = 0.0109$), while choice probabilities of each rural, urban, and CBD zones drop an average of 0.0086, 0.0020, and 0.0003 (from Table 4: $0.4799 - 0.4713 = 0.0086$, $0.1171 - 0.1151 = 0.0020$ and $0.0026 - 0.0023 = 0.0003$). 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 new home buyers than reduced travel time when they are changed by the same proportion or percentage. For example, the estimated average 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.

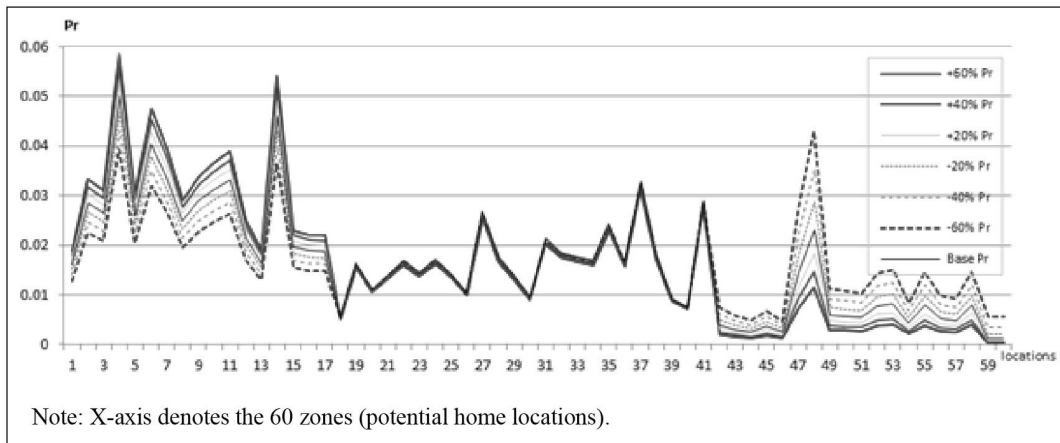
Scenario 5 explores the effect of home price on people's home location choices and welfare. As displayed in Figure 3, the shares of location choice in suburban zones are less sensitive to home price shifts (as compared with all other zone types). For example, zones 10, 37, 48, and 60 exist in rural, 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, respectively, compared with their original probabilities, shown in Table 3: 0.0312, 0.0328, 0.0230, and 0.0013). 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, with superscripts) 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).

Table 5: Welfare Effects of Changing Travel Costs, Times, and Home Prices

(Income = \$70,000, Household size = 2.4 persons, VOTT = \$12/hr)

Changes Scenarios	+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	\$186,079
Auto GC¹	-\$80,661	-\$60,847	-\$34,755	\$46,993	\$112,094	\$206,804
Home Price¹	-\$174,640	-\$124,185	-\$72,106	\$38,989	\$99,511	\$176,764

¹ These results presume VOTT = \$15/hr

Figure 3: Changes in Zone Choice Probabilities Following Home-Price Changes

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 focuses 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 home buyers' 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 household welfare, with an emphasis on new buyers (rather than existing owners, who are also affected by personal-wealth changes, when the values of their existing properties shift, following AI changes).

Home buyer (or residential locator) welfare estimated via logsum differences are estimated to be very small due to changes in the generalized cost of transit; and location choice probabilities remain very stable when raising or lowering all transit travel time and/or cost values. In most U.S. settings and many other regions of the world, access costs via automobile are very important for home location choice. Decreasing travel costs and/or travel times have a more significant impact on home buyer welfare than increasing them; and the higher the AIs, the larger the buyers' choice probabilities in most rural and suburban areas. It is also implied that in urban and CBD areas, home buyers usually pay more attention to home price or home size. The relative significance of home price changes on home-buyer welfare is apparent, as compared with similar (scaled) shifts in the values of other attributes: new locators benefit more when home prices fall by the same amount, both in dollar terms and percentage terms.

These findings are meaningful for many stakeholders 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. Land values and home prices are a major economic policy concern for growing and popular regions, as rents rise and welfare can fall, even if transportation systems are being improved. The London region, San Francisco Bay Area, Auckland, and even Austin, Texas, face serious social and economic issues relating to housing and transport. This paper provides a method for and realistic examples of a holistic view that educates planners, economics, engineers, and policymakers.

Of course, the analysis pursued here illustrates only a limited number of idealized scenarios under a nested logit model structure, and focuses on home buyers rather than renters. 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. One could use Bina et al.'s (2006) parameters for renters' location choices and parameters for rent variations across locations and dwelling types to anticipate welfare impacts on this other very important class of locators. 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.

A variety of other, and ideally more realistic, changes to the transportation system would be very useful to explore here to further describe the changes in AIs, choices, and welfare levels. The possibilities are limitless, and the big changes simulated here, across the zone system, may provide upper bounds on the magnitudes of experience one might expect, which can be useful for evaluating shocks like major recessions (when travel demands fall substantially) or expansionary periods, and changes in transport technology (e.g., self-driving cars lowering perceived travel costs dramatically). The future is always uncertain, but it is wise to anticipate land price and welfare effects well in advance to shape policies and practices that enhance local and regional communities.

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Endnotes

1. Logsums are the natural log of summations of exponential functions of the systematic utilities across alternatives, under a logit-choice-model specification. Logsum differences quantify changes in expected maximum utilities and thus consumer surplus before and after the change.
2. 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.
3. The rule-of-half method (RoH) is a traditional method for calculating consumer surplus in transport economics. It assumes that the consumer demand curve is linear with respect to generalized costs, at least between original and new demand values. When generalized cost changes from GC^0 to GC^1 , travel demand (in the form of person-trips) will change from T^0 to T^1 . The change in consumer surplus (ΔCS) can be computed as follows:

$$\Delta CS = \frac{1}{2}(T^1 + T^0)(GC^0 - GC^1).$$

4. 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 (square feet)-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 $\alpha_2 = 3.34/2.4 = 1.39$.
5. Kockelman and Lemp (2011) relied on a four-layer (destination, mode, time of day, and route) NL model, with scale parameters ($\mu_1, \mu_2, \mu_3, \mu_4$) 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).
6. Skim files are optimal/shortest travel times and costs between all origin-destination pairs, by mode, following a loading of demand onto the network, and solving for a user equilibrium, where no one can improve his/her generalized cost of travel.
7. 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.

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Shuhong Ma is an associate professor in the Traffic Engineering Department School of Highways at Chang'an University. Ma's main research interests are transportation planning and policy-making, system evaluation, and traveler behavior in response to pricing and policy. She has been, and continues to be, involved in many projects in this area and has published extensively in this area of research. Ma's current research focuses on the relationship between accessibility and public transit system in Xi'an City. Prior to teaching and researching at Chang'an University, she obtained her BS in 1999 and master's in 2002 in transportation engineering from Chang'an University. In 2008, she received her doctoral degree.

Kara Kockelman is a registered professional engineer and holds a PhD, MS, and BS in civil engineering, a master's of city planning, and a minor in economics from the University of California at Berkeley. Dr. Kockelman is primary and co-author of over 140 journal articles (and one book) across a variety of subjects, nearly all of which involve transportation-related data analysis. Her primary research interests include planning for shared and autonomous vehicle systems, the statistical modeling of urban systems (including models of travel behavior, trade, and location choice), energy and climate issues (vis-à-vis transport and land use decisions), the economic impacts of transport policy, and crash occurrence and consequences.