Residential Location Choice in the Era of Shared Autonomous Vehicles

ABSTRACT

Shared Autonomous Vehicles (SAVs) is a promising future travel mode, as it significantly improves accessibility while reducing transportation costs. This hypothetical study examines potential changes in residential location choice when SAV (one of the many potential deployment forms if AVs) becomes a popular mode of travel in the Atlanta Metropolitan Area. To accomplish this goal, this study uses an agent-based simulation approach, which integrates residential location choice models with an SAV simulation model. The coupled model simulates new home location choices given current home location preferences and real estate development patterns, as well as expected reductions in relative transportation costs. The results indicate that commuters may relocate to neighborhoods with better public education resources and preferable built environment features, as they will be less attached to their work locations due to reductions in commute costs. The results suggest that SAVs, if encouraged by appropriate travel demand management policies and land use regulations, can help curb sprawl, as the high waiting time in the suburban areas makes these locations less appealing for home buyers. The model results also show that magnitude of change depends heavily on the perceived in-vehicle travel time costs in the era of SAVs.

Key words: Shared Autonomous Vehicles, Residential Location Choice, Urban Form, Sprawl

INTRODUCTION

The advances in self-driving technology are creating both excitements as well as anxieties about the future of urban transportation. In fact, 30 vehicle manufacturers or IT companies have obtained permits and are testing their Autonomous Vehicles (AVs) in real-world conditions (Hawkins 2017). There are multiple ways (and combinations of ways) that this transformational technology can be deployed (Litman 2014). Some envision this technology to be combined with the shared economy, which will enable a new door-to-door transportation mode – Shared AVs (SAVs) (Krueger, Rashidi, and Rose 2016b). Some expect the SAVs to complement existing transit systems, by serving as first/last-mile connections to current transit stations (Y. Shen, Zhang, and Zhao 2017). Others speculate that privately-owned AVs (PAVs) may dominate the market, given existing stated preference survey results (Bansal, Kockelman, and Singh 2016) and can result in approximately 13% more VMT generation (Zhang, Guhathakurta, and Khalil 2018). Regardless of the form of AV deployment, this disruptive technology will fundamentally change the way people travel, which will, in turn, transform patterns of urban development.

Among all the AV deployment models, SAV is recognized as a promising future transportation mode that can significantly reduce commuting costs by eliminating vehicle ownership costs and travel time costs (Burns, Jordan, and Scarborough 2013; Bridges 2015; Albright et al. 2016; Barclays 2016). Experiments conducted in Singapore (NuTonomy 2016), Pittsburgh, US (Coyne 2015), Milton Keynes, UK (Curtis 2016) and several other cities in Europe (CityMobil2 Project 2016) suggest that this technology is maturing quickly. Meanwhile, the policy environment in the U.S. is also catching up to lay the groundwork for vehicle automation technology. For instance, U.S. Department of Transportation has announced a new policy to prepare for larger scale deployment of AVs (U.S. Department of Transportation 2016). In addition, several recent stated preference studies suggest potentially rapid market penetration of SAVs, in particular among the younger generation and multi-modal users (Bansal and Kockelman 2016; Bansal, Kockelman, and Singh 2016; Krueger, Rashidi, and Rose 2016a, 2016b).

This disruptive travel mode will undeniably alter residential location choices and ultimately trigger different land use patterns. Urban development history and theory suggest that innovations in transportation technology lead to significant land use changes, from the invention of streetcars to the introduction of internal combustion engines. Early bid-rent models (von Thünen 1826; Alonso 1964) and more recent discrete choice models (Schirmer, van Eggermond, and Axhausen 2014) indicate that changes in transportation costs and land accessibility will fundamentally alter people's location decisions and arguably lead to a leap-frog urban development pattern. Feedback from a recent stated preference survey from Austin, TX, suggests that there will be various shifts in residential location choices by different market segments in the SAV scenario (Bansal, Kockelman, and Singh 2016). However, little study has focused on how an SAV system will affect residential land use. More specifically, this study examines the question: Will the SAV system induce urban sprawl or encourage compact development?

To address the research question, this study integrates an existing SAV simulation model (Zhang and Guhathakurta 2017) with a residential location choice model. The model will examine residential location choice changes under the assumption that SAV is the predominant travel mode in the future. The combined model is then implemented using data from Atlanta Metropolitan Area. First, the residential location choice model is developed using 2011 Atlanta Travel Survey and Zillow data. The model reveals current preferences of commute time costs and vehicle travel expenses in home location choices. The SAV simulation model is implemented using Atlanta 10-county network and Origin-Destination (OD) matrix to assess new transportation costs after the introduction of SAVs. Residential location choices in the SAV scenario are then evaluated by updating the previous model results using the SAV transportation costs by four market segments. The following sections describe the latest SAV and residential location choice modeling efforts, model construction, model implementation, key findings from multiple scenarios, and conclusions respectively.

EARLIER STUDIES

Previous studies confirm that SAVs can accommodate partial or entire travel demand in many cities worldwide, including Austin (Fagnant, Kockelman, and Bansal 2015), New York (W. Shen and Lopes 2015), Lisbon (Martinez, Correia, and Viegas 2015), Singapore (Spieser et al. 2014), and Stockholm (Rigole 2014). Simulation results also suggest the SAV system can reduce Greenhouse Gas (GHG) emissions and save energy from a life cycle perspective (Fagnant and Kockelman 2014; Greenblatt and Saxena 2015), despite excessive VMT generation. Some studies also suggest that the surplus VMT generation can be curbed or even eliminated via ride-sharing services (Fagnant and Kockelman 2015; Zhang et al. 2015b). Additionally, the SAV system can also reduce a substantial amount of parking lots (Zhang et al. 2015a; Zhang and Guhathakurta 2017).

In addition to the discussed benefits, the system is also found to be more affordable compared to the existing privately owned vehicles and prevailing ride-sourcing services. Burns, Jordan, & Scarborough (2013) suggest that the cost of SAVs can range from ¢15-41/mile based on the trip generation density and SAV fleet size. More recent reports indicate a similar variety of costs for SAVs. Barclays (2016) forecast the cost to be ¢29/mile given the reduction in insurance, operation, and maintenance. Researchers from KPMG estimate the cost can be as low as ¢17/mile (Albright et al. 2016). Bridges (2015) suggest that electricity powered SAV system can still anticipate reasonable marginal profits with a fare of ¢13/mile. In short, the SAV fare may range from ¢13-40/mile based on various assumptions in technology development and insurance reduction rates. Even the highest SAV fare estimation remains considerably less than the cost for average sedans, which is ¢75/mile (AAA 2016). In sum, the SAV costs can be significantly lower due to reductions in insurance, maintenance (as AVs are safer), and operation (as AVs can operate more efficiently with eco-driving mode), as well as elimination of vehicle ownership costs, such as depreciation.

Besides the mile-based cost reduction, the SAV can also significantly reduce travel time costs. Given the possibility of multi-tasking in vehicles, the in-vehicle travel time (IVTT) will no longer be a nuisance to drivers. Therefore, the future transportation costs will be a combination of discounted IVTT costs and out-of-vehicle travel time (OVTT) costs. The expected SAV waiting time or OVTT at different parts of the region may vary given the availability of the vehicles. Despite the SAV relocation strategy, the SAVs may still concentrate in zones with higher destination density, especially those highly developed or populated zones. Therefore, clients hailing for service in densely developed zones may experience shorter waiting time than their peers in suburban areas. Although the OVTT may differ throughout the region, it is certain that SAVs can dramatically reduce travel time costs by reducing or even eliminating IVTT time costs.

There is an extensive literature on the relationship between transportation costs and household's residential location choice. The early land use models are based on microeconomic theories and can be traced back to 19th century. von Thünen (1826), and later Alonso (1964), developed the bid-rent model that explained how transportation costs co-vary with land rents, land use, and the intensity of land development. Their models predicted the formation of rings of zones with different land uses around the employment center with some variation along transportation corridors. These models only considered the monocentric urban structure and assumed homogenous land characteristics throughout the region.

More recent empirical studies have utilized advanced discrete choice models and simulation techniques to relax the assumptions in von Thünen and Alonso's models. Despite different research methodology, most recent studies also reveal that transportation costs are significantly correlated with residential location choices. Commuting time has a negative impact on the utility function (Guo and Bhat 2007; Zhou and Kockelman 2008; M. Habib and Miller 2009; Lee et al. 2010). Other studies have differentiated commuting time for private vehicles and public transit and both variables turn out to be negative and significant in explaining residential location choices (Pinjari, Bhat, and Hensher 2009; Pinjari et al. 2011). One study suggested that commuting time by transit is a more critical factor than commuting time by private automobile (de Palma, Picard, and Waddell 2007).

The literature discussed above clearly indicates that residential location choice will be affected by the low cost and high convenience of SAVs when they are widely available. However, we know little about how SAVs will change residential location decisions given that few studies have undertaken this work. This study addresses this gap by integrating a residential location choice model with an SAV simulation model to examine changes in home location choices. The models are implemented using data from the Atlanta Metropolitan area.

METHODOLOGY

This study uses a three-step model framework. The first step develops a residential location choice model to reveal the existing residential choice preferences of households in different market segments. The residential choice preferences include property-level characteristics, built environment features, and various commuting costs, such as commute time costs and commute travel costs. The second step involves developing an SAV simulation model, which uses SAVs to fulfill the travel demand in the region. The simulation model outputs Traffic Analysis Zone (TAZ) level OVTT. The commute costs derived in Step 1 are then updated using outputs from the SAV model. The third step is to plug the new commute costs, obtained in Step 2, back to the residential location choice model, evaluated in Step 1, to simulate the distribution of new residential location choices using the Monte Carlo simulation method. Each step of the model is elaborated in the following sections.

Step 1: Residential Location Choice Models

The widely used McFadden's MNL model (1978) is applied to estimate the preferences in residential location choices. In the MNL model, the probability of a household n choosing any property i across J alternatives can be expressed as:

$$P_{ni} = \frac{e^{V_{ni}}}{\Sigma_{j=1}^{J} e^{V_{nj}}} \tag{1}$$

The utility of household n choosing property i, denoted as V_{ni}, in the above equation can be written in a linear-in-parameter form as follow:

$$V_{ni} = \beta_1 \boldsymbol{T_{ni}} + \beta_2 \boldsymbol{Z_i} + \beta_3 \boldsymbol{X_{ni}} + \boldsymbol{\epsilon_{ni}} \tag{2}$$

Where, $\boldsymbol{T_{ni}}$ is a vector of commuting cost for household n at the property i. $\boldsymbol{Z_i}$ is a vector of property attractiveness measures, such as features of property i and characteristics of the built environment/ neighborhood where the property i is located. $\boldsymbol{X_{ni}}$ represents interaction terms of socio-economic and demographic characteristics of household n with the attractiveness of property i. β_1, β_2, and β_3 are vectors of estimated coefficients. $\boldsymbol{\epsilon_{ni}}$ is unobserved random utility components for each decision maker i given the property n. This component is independent and identically Gumbel-distributed (McFadden 1978). The model is estimated using the *mlogit* package in R software (Croissant 2010). Rather than exhausting all the alternative properties on the market, the model randomly samples 29 properties, denoted as C', from the entire choice set C as the modeled choice set. McFadden (1978) indicated that consistent estimations of coefficients could be achieved with a random sampling of all potential choices.

The commute costs for household n choosing the alternative i, denoted as $\boldsymbol{T_{ni}}$, are calculated based on the location of the property and work location(s) of the households. $\boldsymbol{T_{ni}}$ is decomposed into two parts, namely the commute time costs and commute travel costs, as shown in Equation 3. The commute time costs for household n choosing alternative i are calculated by multiplying the aggregated commute time of all workers (denoted using k) by the hourly salary, as shown in Equation 4 below.

$$T_{ni} = \; Commute\ Time\ Cost_{ni} + Commute\ Travel\ Cost_{ni} \tag{3}$$

$$Commute\ Time\ Cost_{ni} = \sum_{k=1}^{K} t_{n_k i} * Salary_n \tag{4}$$

The commute travel costs are calculated by multiplying the vehicle costs per mile by the aggregated travel distance. The vehicle costs include 1) vehicle ownership costs, such as depreciation, insurance, taxes, licenses and registration fees, and 2) operation costs, including gas per mile, maintenance, and tires. The vehicle ownership cost and operation cost are summarized in Table 1 (AAA 2010).

Table 1: 2010 Vehicle Ownership and Operation Costs by Vehicle Type

	Annual Ownership Cost	Operation Costs (per mile)
Small Sedan	$4,381	$0.141
Medium Sedan	$5,841	$0.173
Large Sedan	$7,707	$0.188
Sport Utility Vehicle	$7,738	$0.223
Minivan	$6,404	$0.193
Pickup Truck*	$7,071	$0.208

* pickup truck cost is estimated as the average of SUV and Minivan

The mile-based vehicle ownership cost is estimated by normalizing the total vehicle ownership cost with the annual mileage, which is assumed to be 15,000 per vehicle (AAA 2010). The household mile-based vehicle ownership is the sum of all normalized vehicle ownership costs. The operation cost is estimated as the average of vehicle operating costs for all the owned vehicles, denoted as V. The final vehicle cost for household n is estimated by adding the aggregated vehicle ownership with the averaged vehicle operating cost, as shown in Equation 5. The vehicle costs are positively correlated with the size of the vehicles, i.e., the larger the owned vehicles, the more expensive the vehicle costs are for the household. The final commute travel cost for household n choosing alternative i is estimated by multiplying the total commute distance for all workers in the household with the household's vehicle cost (see Equation 6).

$$Vehicle\ cost_n = \frac{\sum_{v=1}^{V} Ownership\ Cost_v}{15{,}000 * V} + \frac{\sum_{v=1}^{V} Operation\ Cost_v}{V} \tag{5}$$

$$Commute\ Travel\ Cost_{ni} = \sum_{k=1}^{K} d_{n_k i} * Vehicle\ cost_n \tag{6}$$

Both commute time $t_{n_k i}$ and distance $d_{n_k i}$ are obtained using Google Distance Matrix Application Programming Interface (API) given the location of property i and work location of work k in household n.

We used an exogenous market segmentation method to divide the housing market into different clusters to address the heterogeneity in home location preferences. First, households are clustered based on socio-demographic and economic variables, such as age, life cycle, and income. Then segmented MNL models are implemented to derive log likelihoods and estimate coefficients. The results are then checked using 1) Chi-square tests (shown in Equation 7) to determine significant improvement in the segmented model compared with the pooled model; and 2) t-tests (shown in Equation 8) to verify that coefficients differ across groups (Ben-Akiva & Lerman, 1985, p.202-204). Although this market segmentation method is deterministic and arbitrary, it is considered robust enough in the residential location choice literature. For instance, the UrbanSim model uses this exogenous market segmentation method (Waddell 2002; Waddell et al. 2007) as do other empirical studies (K. N. Habib and Kockelman 2008; Zhou and Kockelman 2008).

$$Chi-square\ Test\ Score = -2\left(L(\hat{\beta}_{pooled}) - \sum_{g=1}^{G} L(\hat{\beta}_g)\right) \sim X^2_{(G-1)K,\alpha} \tag{7}$$

Where, $L(\hat{\beta}_{pooled})$ is the log likelihood for the pooled model; $L(\hat{\beta}_g)$ indicates the log likelihood for the g^{th} market segment; G indicates the total number of market segments; K is the total number of explanatory variables used in the models; and α denotes the significance level of the test.

$$t - test\ Score = \frac{\widehat{\beta_k^i} - \widehat{\beta_k^j}}{\sqrt{Var(\widehat{\beta_k^i}) + Var(\widehat{\beta_k^j})}} \sim t_{N-GK} \quad (8)$$

Where, $\widehat{\beta_k^i}$ indicates the estimated coefficient for the k^{th} variable from i^{th} market segment and the t-test has a degree of freedom calculated from sample size (N) subtracted by total number of estimated coefficients (GK).

Step 2: SAV Simulation Model

The SAV simulation model used in this study has been described in another Atlanta-based SAV simulation study (Zhang and Guhathakurta 2017). The model recreates virtually a scenario in which SAVs are assigned to fulfill the travel demand generated by residents. The spatial resolution of the simulation is the Traffic Analysis Zone (TAZ). The model first randomly generates trips based on the local Origin-Destination (OD) matrix from the four-step travel demand model. The departure times of trips follow the distribution obtained from the weighted local travel survey. The first-day simulation is used as a “warm-up” simulation to determine the fleet size and, therefore, is excluded in the final analysis. At the beginning of the first simulation day, the model randomly distributes 10,000 vehicles in the region. Each time a client waits for more than 15 minutes, the model adds one more vehicle to the system to fulfill the demand immediately. The model always assigns the SAV with the least waiting time cost to serve incoming clients. The client will be put on a waiting list if all SAVs are occupied and will be prioritized for service once a vehicle becomes available again. After dropping off clients, the idling SAVs will be assigned either to relocate to underserved areas or to park directly. Such decision to continue relocating or to park is made based on the overall spatial distribution of available SAVs in the system. After 50 simulation days, the model will summarize the average waiting time (i.e., the time from calling for service to picking up) for clients originating at different TAZs, excluding the first-day results. To simplify the modeling process, no ride-sharing is considered in this model. This agent-based simulation model is implemented in Python. Each simulation day takes approximately 2 CPU hours to finish on a computer with 2.6 GHz Intel Core i7 and 16 GB of memory.

After the introduction of SAVs, the commute time cost will no longer be dominated by the IVTT costs, but rather by the summation of the OVTT costs at the origin of the trip and discounted IVTT costs, as the clients can multi-task in the vehicle. Therefore, the commute time cost for household n to choose alternative i can be re-estimated as the sum of expected waiting time in TAZ i and TAZ k, where worker k's workplace is located, and partial (α) of the IVTT costs, multiplied by the household hourly salary, as shown in Equation 9. We tested α ranging from 0% up to 75% to determine the marginal effect of such a parameter on residential location choices.

$$Commute\ Time\ Cost'_{ni} = \sum_{k=1}^{K} (OVTT_i + OVTT_k + \alpha * IVTT_{i,k}) * Salary_n \tag{9}$$

The commute travel costs are re-estimated by multiplying the total commute distance by the SAV cost per mile, as shown in Equation 10. The SAV costs per mile are approximated using results from various SAV costs simulation studies. In this study, the ¢30/mile fare is adopted to update commute travel costs in the SAV scenario.

$$Commute\ Travel\ Cost'_{ni} = \sum_{k=1}^{K} d_{n_k i} * SAV\ Cost/Mile \tag{10}$$

Step 3: Residential Location Choice using Monte Carlo Simulation

This step updates the residential location choice model results using the new transportation costs, T'_{ni}, obtained from the SAV simulation model. The probability of selecting each alternative can be expressed as follows:

$$P'_{ni} = \frac{e^{V'_{ni}}}{\Sigma_{j=1}^{J} e^{V'_{nj}}} \tag{11}$$

$$V'_{ni} = \beta_1 \boldsymbol{T'_{ni}} + \beta_2 \boldsymbol{Z_i} + \beta_3 \boldsymbol{X_{ni}} + \boldsymbol{\epsilon_{ni}} \tag{12}$$

The new cumulative density function for household n, CDF_n, can be obtained by accumulating P'_{ni} over all alternatives. The distribution of new residential location choices is then generated using the Monte Carlo simulation approach as below.

$$r = random.uniform(\,) \tag{13}$$

$$new\ choice_n = CDF_n^{-1}(r) \tag{14}$$

Where, r is a uniformly distributed random number ranging from zero to one. The new residential choice for household n can be simulated by plugging r back into the inverse CDF for household n. This process is repeated for 1,000 times to obtain a representative distribution of new choices.

MODEL IMPLEMENTATION

Data for Residential Location Choice Model

The residential location choice model is implemented with the help of data from the Atlanta Regional Commission (ARC) 2011 travel survey and real-estate property records from Zillow. The 2011 Atlanta travel survey includes socio-economic and demographic information for 6,736 households with workers living in the 10-county metropolitan area. The survey samples are collected from November 2010 to January 2011. ARC has already geocoded Worker's home and office addresses in the survey. Therefore, the travel survey offers information of the residential location choice at the time the survey was conducted. However, the travel survey does not provide information regarding the characteristics of the properties, the property transaction date nor the property choice set available when the household was in the market for housing. These missing pieces of information are collected from the Zillow website using Zillow *GetDeepSearchResults* API. For each sampled household in the travel survey, the property record at their home location is obtained from Zillow. Zillow maintains a 10-year record of sale for each property. The property purchase date is then determined as the closest sale record before the travel survey date since we know that the sampled household lived at that address at the time the travel survey is conducted. To avoid dramatic changes in the socio-economic status of the households, only households who have purchased the property within a 5-year period before the reported survey date are included in the final model.

After joining the Zillow data with the travel survey data, we excluded some households due to unreasonable combinations of home and work location (e.g., estimated commuting time significantly larger than reported commuting time), property values, and property characteristics. Additionally, we also removed households who *exclusively telecommute*. This is because telecommuting households are unlikely to experience changes in commute related transportation costs, rendering the developed model insufficient to capture potential changes in their residential location choices. Finally, we eliminated households who commute on MARTA or local transit, which consisted approximately 2.3% of the sample. These households were excluded since the process involves more complex models for simultaneously modeling commute mode choice and home location choice, which is redundant for the vast majority of the properties not served by

MARTA. Eventually, there are 909 households in the final model data set. The final sampled households are evenly distributed in the 10-county metropolitan area.

For each sampled household, residential location alternatives are generated by randomly choosing from properties that have been transacted within the one-year time window. Housing units that have been transacted 6-month before or after the actual purchase date are all considered as a potential choice set, which includes both new constructions and existing housing units available for sale. For each household, we randomly select 30 housing units from the possible choice set (including 29 randomly sampled and one observed selection) as the alternatives to input into the model. The assumptions behind such random sampling scheme are (1) home buyers have bounded rationality, therefore, cannot exhaust all the potential alternatives on the market and (2) development pattern will continue in the future (i.e., there won't be significant changes in zoning and land use regulations in the era of SAVs).

Four types of explanatory variables are included in the residential location choice models, including the property features, household demographic and socio-economic information, built environment characteristics, and transportation costs. Property features are collected from Zillow website. The GreatSchools Ratings from Great Schools website are used here to reflect the quality of school districts. The household characteristics are obtained from the ARC travel survey. Since the original income variable in the travel survey is categorical, the household hourly salary is imputed as the mid-point of each income category. The built environment variables such as the entropy index and population density are estimated at the TAZ level using 2010 Census data and Longitudinal Employer-Household Dynamics (LEHD) data. The entropy index is calculated using the equation below:

$$entropy_i = -\frac{\sum_{j=1}^{5} p_{ij} * \log\left(p_{ij} + 0.01\right)}{\log(5)} \tag{15}$$

$$p_{i1} = \frac{h_{sf}}{h_{sf} + h_{mf} + job_{all}} \tag{16}$$

$$p_{i2} = \frac{h_{mf}}{h_{sf} + h_{mf} + job_{all}} \tag{17}$$

$$p_{i3} = \frac{job_{reserve}}{h_{sf} + h_{mf} + job_{all}} \tag{18}$$

$$p_{i4} = \frac{job_{prof}}{h_{sf} + h_{mf} + job_{all}} \tag{19}$$

$$p_{i5} = \frac{job_{labor\ intesive}}{h_{sf} + h_{mf} + job_{all}} \tag{20}$$

where,

i is the index for TAZ and j is the index for components in entropy index calculation;

h_{sf} is the number of single family households;

h_{mf} is the number of multi-family households;

job_{reserv} is the number of jobs in the retail/service sector;

job_{prof} is the number of jobs in the professional sector;

$job_{labor\ intensive}$ is the number of jobs in the labor-intensive industries.

In addition to the calculated built environment variables, the Walkscore at the block group centroid is also collected and tested in the model. All the built environment variables are spatially joined to properties using ArcGIS. The transportation costs variables are estimated using Equation 3-5 based on the commuters' work locations from Atlanta Travel Survey and alternative property locations from Zillow. In addition to the four types of explanatory variables, we also calculated alternative specific interacted variables, such as property price-income ratio, percent of the same race in the neighborhood, and square feet per person.

Table 2 summarizes the detailed descriptive statistics for variables and the corresponding data sources. The descriptive statistics are calculated based on the entire input dataset, which contains all alternatives for each household. Therefore, the distributions of alternative specific variables do not reflect the actual distribution of the variable in the real world. For instance, the average commute travel cost is $1,567 per month across all alternatives, which is significantly larger than the average commute travel cost for the eventually purchased properties, which is $1,155 per month.

Table 2: Descriptive Statistics for Independent Variables

Variables	Type	Mean	Std. Dev.	Source
Socio-Economic Variable				
Household Header Age	Cont.	47.11	12.33	
Household Size	Cont.	2.90	1.33	
Annual Income*	Cont.	$76,850	$35,510	
Vehicle ownership	Cont.	2.11	0.88	ATS
# Worker	Cont.	1.62	0.59	
Race	Cat.	Range 1-9		
Life Cycle	Cat.	Range 1-10		
Property Variable				
# Bathroom	Cont.	2.88	1.05	
# Bedroom	Cont.	3.72	1.02	
Finished SQFT	Cont.	2524.54	1134.28	
Lot Size Acre	Cont.	0.52	0.66	
Age of Property	Cont.	19.49	21.18	Zillow
Sale Price	Cont.	$271,114	$178,410	
Sale Year	Cat.	Range 2005-2010		
Sale Month	Cat.	Range 1-12		
Single family (binary)*	Binary	92.94% Single Family		
Primary School Score	Cat.	Range 1-10		
Middle School Score	Cat.	Range 1-10		Great School
High School Score	Cat.	Range 1-10		
Built Environment				
Entropy Index*	Cont.	0.61	0.20	ACS, LEHD
Population Density (per mile^2) *	Cont.	2,503.87	2,524.55	
Employment Density (per mile^2) *	Cont.	917.35	2,048.02	LEHD
Reservation Job Density (per mile^2) *	Cont.	462.61	112.43	
Percent of Occupied	Cont.	0.92	0.05	
Percent White	Cont.	0.58	0.28	
Percent Black	Cont.	0.30	0.29	ACS
Percent Other	Cont.	0.12	0.10	
Median Income	Cont.	$71,907	$31,571	
Distance to Rail Station (mile) *	Cont.	11.33	7.72	MARTA

Distance to Bus Station (mile) *	Cont.	2.17	2.33	
Walk Score (Block Group level)	Cont.	34.36	35.21	Walk Score
Transportation Costs	Cont.			
Commute time costs (monthly) *	Cont.	$488.84	$429.26	Google, ATS
Commute travel cost (monthly) *	Cont.	$1,567.00	$1,028.67	
Interacted Terms	Cont.			
Property Price Income Ratio *	Cont.	4.58	8.51	Zillow, ATS
Percent Same Race *	Cont.	0.48	0.32	
Transportation Costs Income Ratio *	Cont.	0.38	0.55	
Finished SQFT Household Size Ratio	Cont.	1,114.72	864.43	

* indicating computed based on the source data
ATS: Atlanta Travel Survey; ACS: America Community Survey 2010 5-year estimates; LEHD: Longitudinal Employer-Household Dynamics

SAV Simulation Inputs and Parameters Determination

The major inputs of SAV simulation include OD matrices from the ARC travel demand model. There are 1593 TAZs and 9 million vehicle trips in the 10-county study area. Additionally, the matrices also provide spatial distributions of trip origins and destinations. The trip departure time distribution is obtained using the weighted 2011 ARC travel survey. The trip generation peaks between 7-8 a.m. and 5-6 p.m. The link level travel speed is also obtained from the ARC travel demand model. The link level travel speed differs by time of the day, such as morning peak, noon, evening peak and night to reflect congestion during peak hours.

Results from 50 rounds of warm-up simulation runs suggest approximately 367,160 vehicles will be sufficient to serve 10-county travel demand to ensure that more than 99% of the clients can be picked up within 15 minutes after calling for services. The average waiting time is 7.13 minutes on a daily basis. The average waiting time increases to 10.59 during evening peak hours. Each SAV, on average, can serve around 24.5 trips on a daily basis. Additionally, adding more vehicles into the system does not improve the system performance significantly. An SAV system with 5% more vehicles (i.e., 18,358 more) can only reduce the all-day average waiting time by 0.32 minutes to 6.81 minutes. Therefore, for this study, the total fleet size parameter is fixed at 367,160 vehicles for all simulation runs.

MODEL RESULTS

Existing Residential Preferences

The entire population is divided into four market segments based on the household head's age (i.e., elder than 40 or not) and household life cycle (i.e., the presence of children). A chi-square test, as shown in Equation 7, is conducted for the pooled model and the market segment models, using all explanatory variables listed in Table 3. The chi-square test score is estimated as 262.16, which is larger than $X^2_{36,0.05}(\approx 66.7)$. Therefore, the test is significant at the significance level of 5%. The significant chi-square test indicates that the null hypothesis, i.e., the segmented models is no better than the pooled model, can be rejected. Various configurations of market segments, such as groups by income level, by marital status, and by age only, are also examined in this study. However, the chi-square tests for the other combinations of market segments turn out to be less significant or not significant at all. Therefore, these four market segments are adopted in this study.

The residential location choice model results, as shown in Table 3, indicate expected trade-offs between housing or transportation costs and family income, household size, and the presence of children. We tested all variables listed in Table 2, and the insignificant (at the 95% confidence level) variables are removed from the models. The negative signs of the respective coefficients across four models suggest that households prefer newer housing units. The results also indicate that households prefer units with lower prices, shorter commute time, and less total commute costs, as expected. Moreover, the percent of the same race in the block group variable is positive and significant in all models, indicating households self-select to settle in neighborhoods with similar racial profiles. The significant t-test results (see Equation 8) show that the following preferences vary significantly across segments. Households with kids tend to live in better school districts and prefer single-family housing units. Additionally, Elder households with kids also prefer properties in suburban areas where the land use entropy index and population density are lower compared to neighborhoods in or near downtown areas. Many older households without kids seem to also prefer better schools in their vicinity. This is probably because these neighborhoods have better amenities overall since household incomes and housing values are usually correlated with neighborhoods that have better public schools. For example, parks and open spaces are desirable amenities for all ages and are commonly found in areas with good schools. In summary, the model results are reasonable, as the estimated significant coefficients have expected signs according to existing literature. The models also have decent magnitudes of adjusted MacFadden R^2, ranging from 0.268 to 0.347. The commute time costs and the ratio of commute vehicle costs and income in this model will be updated using the SAV simulation model outputs, as discussed in the following section.

Table 3: Residential Location Choice Model Results by Market Segment

	Age<40 & No kids [Beta]	**Age<40 & Kids [Beta]**	**Age>=40 & No kids [Beta]**	**Age>=40 & Kids [Beta]**
Property Age	-0.013 **	-0.033 ***	-0.015 ***	-0.010 *
	[-0.275]	[-0.688]	[-0.329]	[-0.149]
Sale price/Income	-0.226 ***	-0.257 ***	-0.318 ***	-0.220 ***
	[-3.024]	[-1.014]	[-2.751]	[-1.553]
Percent same race (block group)	2.120 ***	3.417 ***	2.279 ***	2.583 ***
	[0.669]	[1.073]	[0.708]	[0815]
Commute time costs	-0.003 ***	-0.005 ***	-0.004 ***	-0.006 ***
	[-1.252]	[-2.180]	[-1.627]	[-2.533]
Commute vehicle costs/Income	-5.541 ***	-4.845 ***	-6.284 ***	-1.761 **
	[-4.698]	[-1.492]	[-3.187]	[-1.024]
Middle school score (3,5]			0.447 *	0.588 *
			[0.176]	[0.280]
Middle school score (5,7]			0.524 *	0.764 *
			[0.192]	[0.280]
Middle school score (7,10)		0.471 *	0.456 *	1.254 ***
		[0.234]	[0.230]	[0.626]

Single family property (binary)		1.748 **		1.229 **
		[0.484]		[0.317]
SQFT per person				0.001 **
				[0.374]
Land use entropy				-0.785 *
				[-0.185]
Population density				-0.0001 ***
				[-0.485]
N	149	144	306	310
Log Likelihood	-330.55	-290.69	-645.63	-681.05
Likelihood Ratio Test	242.24***	305.81***	554.67***	559.98***
Adjusted MacFadden R^2	0.268	0.347	0.300	0.291

*$p < .05$. **$p < .01$. ***$p < .001$

Transportation Costs in the Era of SAV

The SAV simulation results reveal that the average waiting time is negatively associated with the population and employment density in the TAZ, as shown in Figure 1. The spatial distribution of the average waiting time suggests that customers hailing for SAV service in more compact TAZs, i.e., TAZs closer to downtown and highway exists, will experience significantly shorter waiting time than people requesting service in suburban or even rural areas. The average waiting time in downtown and midtown neighborhoods is less than 5 minutes. Meanwhile, customers in the suburban areas in Cherokee, Douglass, Rockdale, Henry, and Fayette counties may expect longer than 10-minute waiting times. In other words, clients in denser areas are more accessible to the SAV system compared to their suburban peers. The results indicate that SAVs may have a limited service boundary and need certain level population/trip generation density to support the efficient operation of the system, similar to the existing transit system.

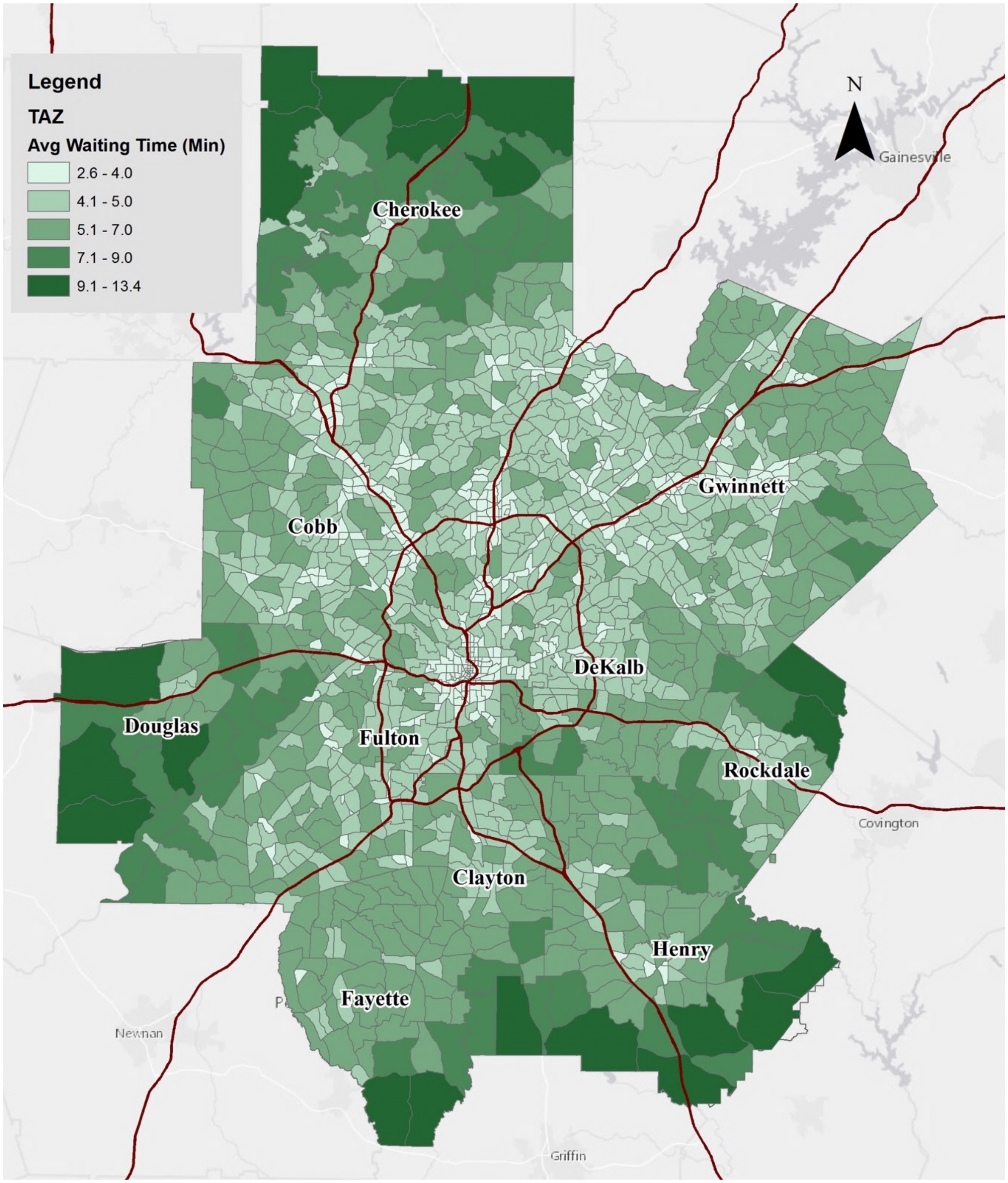


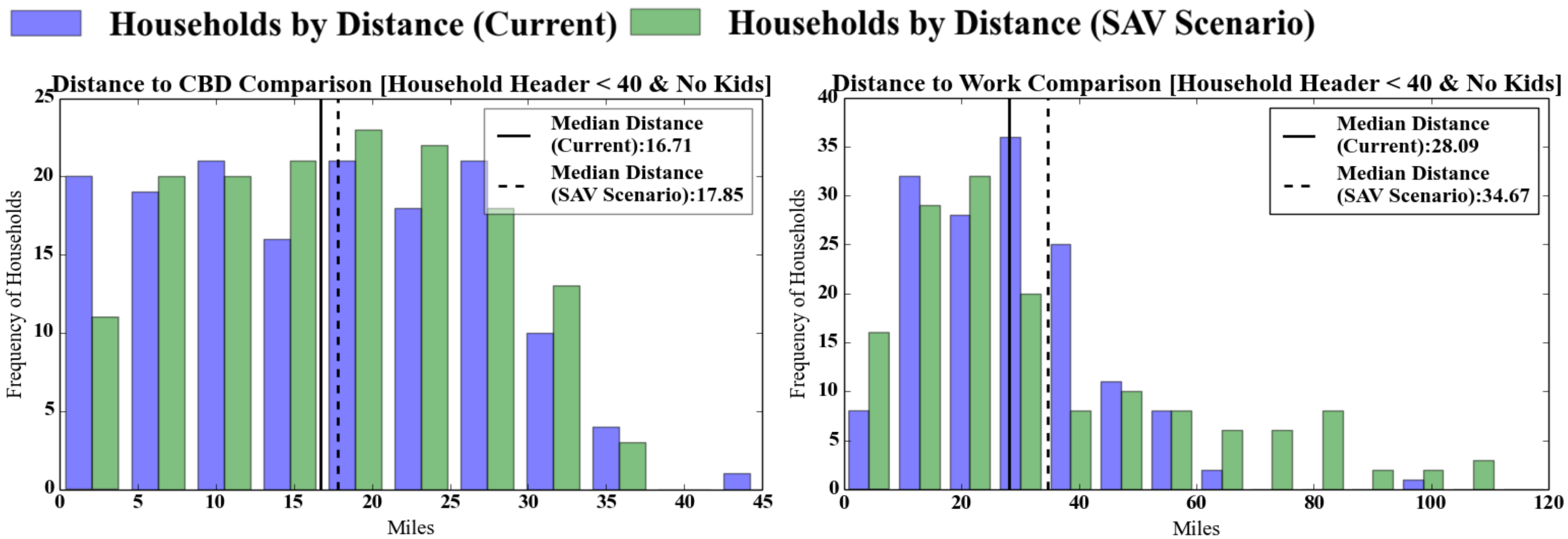
Figure 1: Average Waiting Time by TAZs

The new commute time costs are then estimated using the simulated average waiting time based on Equation 9. In the scenarios, where the IVTT discount factor α equals to 0% (i.e., no IVTT costs will be considered) and 75%, the updated commute time costs are approximately

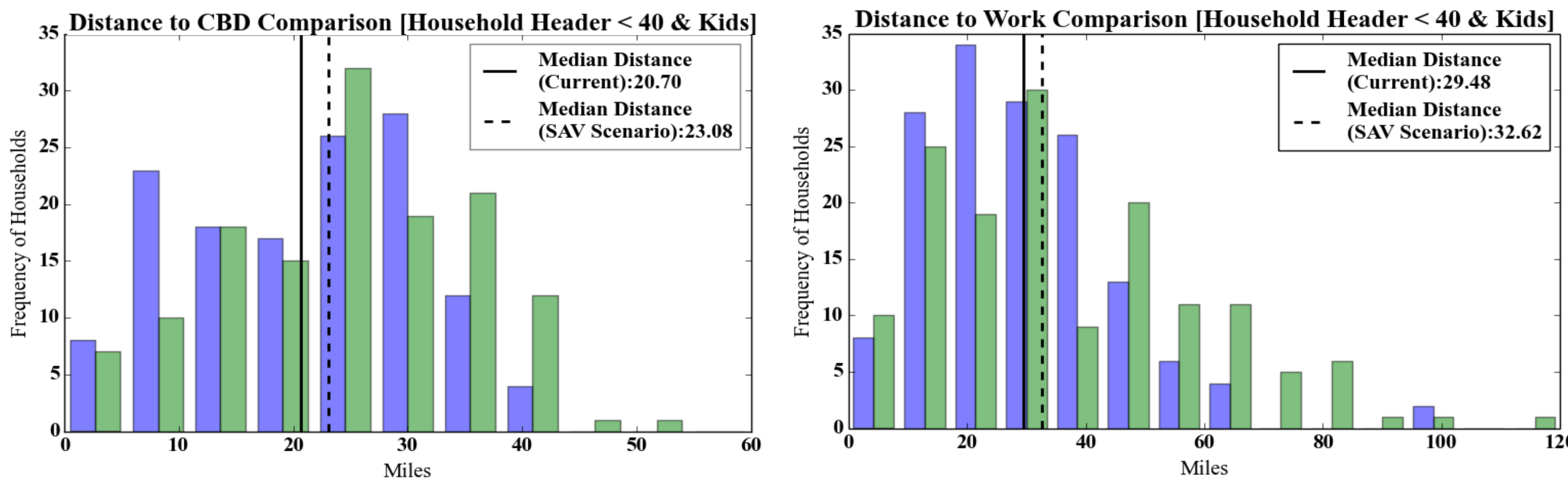
77.1% and 19.3% less than the current costs. Regardless of the magnitude of α, the reductions are most significant for longer commuting trips. The new commute travel costs are calculated with the assumption that SAV fares will be $0.30/mile. The savings in commute travel costs are most significant for households with higher vehicle ownership and inefficient vehicles. The reduction in commute travel costs is, on average, 63.7%. Such reduction builds upon the assumption that households are going to give up their private vehicles and rely exclusively on SAVs (either voluntarily or induced by regulations). The reduction will be less if the households still prefer to own one or multiple private automated vehicles (PAVs) for non-commuting purposes. However, such scenario is not investigated in this study. In summary, the SAVs may reduce 48.4% to 72.5% of the total commute transportation costs for workers, depending on the changes in α from 0% to 75%.

New Residential Location Choices

The Probabilities of choosing each alternative housing unit are then re-estimated using the updated transportation costs variables. New residential location choices are simulated using the Monte Carlo method. The results from the scenario where 0% of IVTT is considered are first compared with the current location choice (as illustrated in Figure 2-3), where the changing trend can be readily observed. The results from other scenarios with α increasing up to 75% are then discussed to examine the marginal effect.

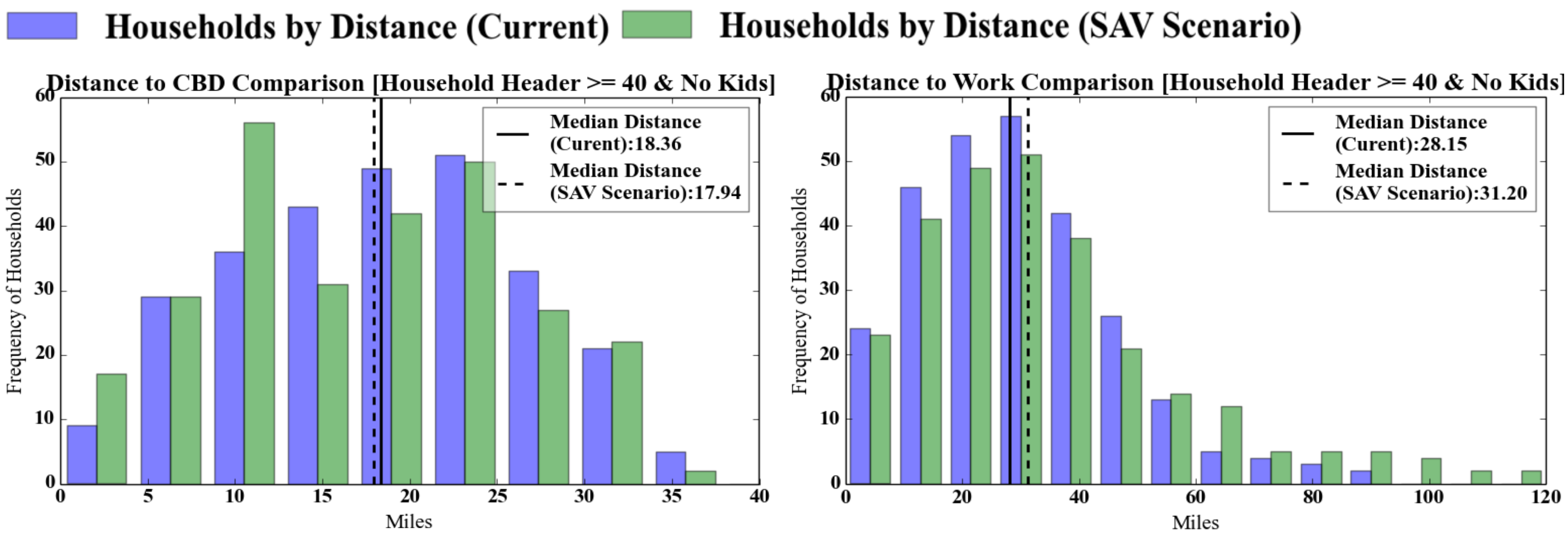


a. Moving Trend for Households younger than 40 and without Kid

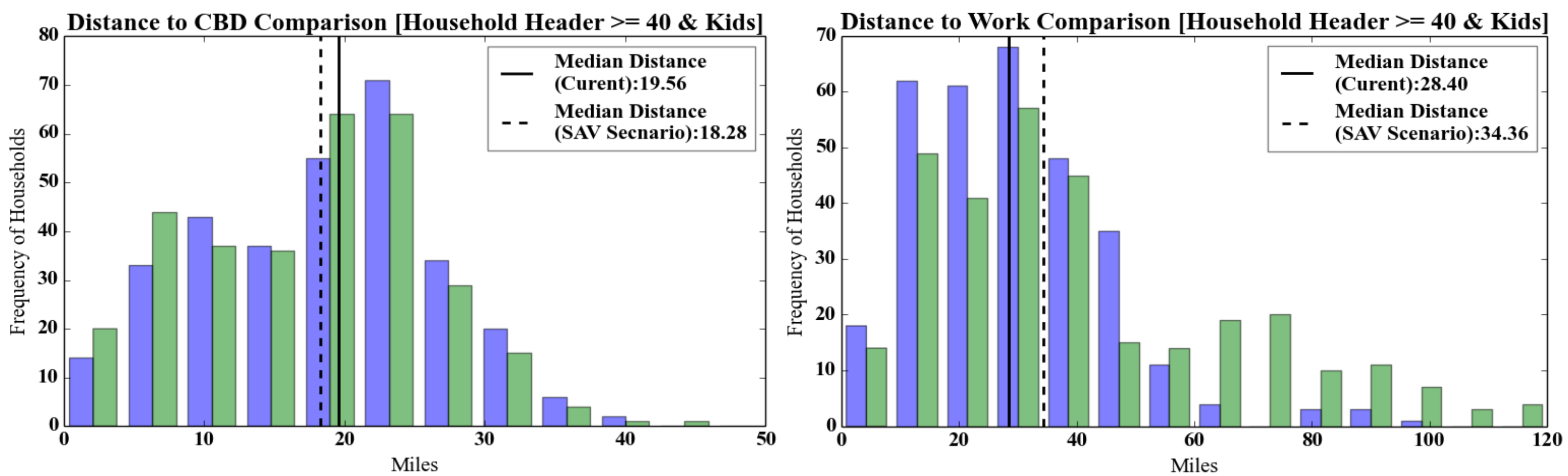


b. Moving Trend for Households younger than 40 and with Kid(s)

Figure 2: Households Location Choices Moving Trend by Market Segment (Age < 40)



a. Moving Trend for Households above 40 and without Kid



b. Moving Trend for Households above 40 and with Kid(s)

Figure 3: Households Location Choices Moving Trend by Market Segment (Age >= 40)

Households, younger than 40 and without kids, on average, will relocate slightly away from the Central Business District (CBD). The observed median distance to CBD is 16.71 miles, while the simulated median distance increases to 17.85 miles. This type of households tends to concentrate in areas that are 20-25 miles away from downtown. Meanwhile, fewer households will live within 5 miles or beyond 25 miles of the CBD area. Therefore, some households are moving away from the downtown area to benefit from the reductions in transportation costs and cheaper housing units that are slightly further away. Meanwhile, a portion of households would move slightly inward to avoid the large waiting time costs in the suburban area. The results also suggest that this type of household is going to live further away from their work locations, as the median distance to work increases from 28.09 to 34.67 miles.

The general moving trend for households, younger than 40 and with the presence of children, is quite similar to their peers without kids. These commuters may also away from their current workplaces with the reduction in commute costs. However, this type of households tends to move further away from CBD area to more remote areas that are more than 40 miles away. This trend may be attributed to the fact that the public education resources in these areas further away are significantly better. They are willing to accept higher overhead waiting time costs to harvest high-quality public education resources for their children. The average school quality score for the selected housing unit increases from 6.6 to 7.1.

Elder households without kids may also move away from their offices in the SAV scenario. However, different from their younger peers, elder households tend to relocate slightly closer to the CBD area, from 18.36 to 17.94 miles. Properties located within 10 miles to the CBD area will be more appealing to these households, due to the smaller waiting time costs in these TAZs. This market segment will also move approximately 3 miles further away from their workplaces for cheaper and newer properties. The median ratio of property price and income decreases from 5.3 to 4.5.

Elder households with children are likely to move slightly closer to the CBD. The median distance to CBD declines from 19.56 to 18.28 miles. Zones that are less than 20 miles to urban core become more attractive to these households. These commuters can afford more expensive properties with better accessibility and school quality due to the significant reduction in commute transportation costs. The selected properties in SAV scenario tends to be more expensive, as the price-income ratio of selected properties increases from 4.79 to 4.85. Compared with elder households without kids, this type of household may move further away from their workplaces, as the median distance to work increases by approximately 6 (20.9%) miles in the SAV scenario.

The marginal effects of changes in perceived IVTT costs are tabulated in Table 4. The results suggest that distance to work and distance to CBD are quite sensitive to the out-of-pocket IVTT costs. Several types of households tend to locate closer to work locations if IVTT cost is higher. Additionally, median distance is greater when the IVTT cost is discounted by more than 50%, that is, this relationship is nonlinear. Assuming that a family has a fixed commute time budget, one-unit reduction in commute time cost can be translated into significantly larger likelihood to purchase properties further away from the workplace.

The changes in median distance to CBD tend to diminish when IVTT is higher. Households with kids tend to be more sensitive to the change compared to households without kids, given that these households have a larger beta for commute time costs. When IVTT costs are lower, households tend to relocate to locations with more desirable location associated characteristics, including the level of land use diversity, density, and school districts. Some households, especially those with kids, prefer better school districts in suburban neighborhoods and move away from CBD areas. Some households find that single family properties closer to downtown can be affordable in the era of SAVs and tend to move closer to CBD area to harvest the location affordability benefits brought by SAVs. Compared with distance to work, distance to CBD is less sensitive to IVTT costs, which is largely because distance to CBD is not significant in MNL models.

Table 4: Median Distance to Office per Worker by various IVTT costs (Miles)

	Market Segment	Observed data 100% IVTT	0%-IVTT	25%-IVTT	50%-IVTT	75%-IVTT
Median Distance to Work	HHs < 40 & No Kids	28.09	34.67	32.49	30.43	29.31
	HHs < 40 & Kids	29.48	32.62	31.27	29.72	29.53
	HHs >= 40 & No Kids	28.15	31.20	28.96	28.36	28.24
	HHs >=40 & Kids	28.40	34.36	31.75	28.97	28.73
Median Distance to CBD	HHs < 40 & No Kids	16.71	17.85	17.10	16.99	16.85
	HHs < 40 & Kids	20.70	23.08	22.19	21.07	21.00
	HHs >= 40 & No Kids	18.36	17.94	18.09	18.23	18.30
	HHs s >=40 & Kids	19.56	18.28	18.98	19.38	19.47

SAV costs ranging from $0.15 to $0.50 per mile are also examined to determine the elasticity of residential location choice with respect to SAV fare. The results, as tabulated in Table 5, indicate that the distance to work is negatively associated with the SAV fare, as workers may move closer to work locations with the increase in SAV fare. Meanwhile, households, younger than 40 without kids, are more sensitive to SAV costs compared to other market segments, given that the largest reduction in distance to work per unit increase in SAV fare is found for this market segment. This can be attributed to the fact that this market segment has the largest estimated betas for the vehicle travel cost and income ratio variables.

Table 5: Median Distance to Work and CBD per Worker by SAV fares (Miles)

	Market Segment	Observed data (See Table 1)	SAV - ¢15/mile	SAV - ¢30/mile	SAV - ¢50/mile
Median Distance to Work	HHs < 40 & No Kids	28.09	36.58	34.67	32.33
	HHs < 40 & Kids	29.48	33.80	32.62	30.88
	HHs >= 40 & No Kids	28.15	32.16	31.20	29.84
	HHs >=40 & Kids	28.40	34.80	34.36	33.55
Median Distance to CBD	HHs < 40 & No Kids	16.71	18.93	17.85	16.96
	HHs < 40 & Kids	20.70	23.55	23.08	22.09
	HHs >= 40 & No Kids	18.36	17.70	17.94	18.13
	HHs s >=40 & Kids	19.56	17.89	18.28	18.98

In summary, the results suggest that all market segments are going to be less attached to their workplaces. The properties with preferred structural characteristics, school districts, and neighborhood features will become more appealing to home buyers. Therefore, the SAV induced reduction in transportation costs provides more freedom for home buyers regarding where they may live in the region. Meanwhile, the results also indicate a significant increase in the commute VMT, as the median commute distance per commuter increases for all market segments, ranging from 11% to 23%. However, this finding does not include VMT generation for other trip purposes and, therefore, cannot predict what overall VMT changes might be with the popularity of SAVs. Moreover, different scenario results also indicate that the assumptions of SAV fare costs and perceived IVTT costs will only affect the magnitude of the changing trend and are not likely to change the direction of the noted changes in residential location choices.

CONCLUSIONS

In this paper, we developed a residential location choice model, which was updated with transportation cost parameters from a discrete-event agent-based SAV simulation model to examine potential changes in residential location choices in the era of SAVs. The results suggest that most of the households may move away from their workplaces and relocate to neighborhoods with more appealing property characteristics and better schools. Therefore, the SAVs will provide more freedom in location choices for home buyers.

The model outputs also suggest that SAVs, to some extent, can help curb urban sprawl. First, SAVs can make compact development more appealing by offering more convenient services with less average waiting time in densely developed neighborhoods. The simulation results show that the elder generations are likely to move slightly closer to CBD area to avoid significant waiting time costs in suburban locations. Although the younger generations are likely to move away from the downtown area in the era of SAVs, the majority of this market segment still prefers to locate within the 25-mile network buffer to CBD area. This model does not incorporate other travel modes. Without proper policy and regulation interventions, it seems that suburban residents may not embrace SAV, given the long waiting time. Therefore, to utilize SAVs to battle urban sprawl, policy makers need to subsidize the operation of SAVs while penalizing the PAV ownership and also revise existing zoning ordinance and land use regulations to curb new development in rural areas and encourage infill development in the urban core (especially reuses redundant parking lots in the future).

The model outputs also reveal an increase in commute VMT generation across all market segments. The larger VMT footprint will result in more congestion, more operational energy consumption Greenhouse Gas (GHG) emissions. To address excessive VMT generation, policies for transportation demand management, including encouraging the use of transit and carpooling services, are necessary. Meanwhile, it remains unclear whether the VMT generation for other trip purposes will change with the popularity of SAVs, which could be the subject of further research. However, the overall higher generation of VMT may not necessarily indicate transportation system will be less sustainable in the future. The life cycle energy consumption and GHG emissions of the SAV system are estimated to be significantly lower than the current system, as one SAV is capable of replacing 9-13 current vehicle ownership. Future studies may also explore the impact of transit complementary SAV system (i.e., an SAV that only serve clients to/from rail stations) to identify more sustainable business models of SAVs.

Some limitations of the models presented merit future research efforts. First, SAV is the only modeled travel mode in this model, mode choice among SAV, privately owned AV, and transit is not considered. Different model choice can significantly change the commute transportation costs, which may reverse the trends in residential location choices. Second, the trip assignment model is not included in this study. Therefore, it is assumed that congestion levels will be the same as business as usual. However, SAV system tends to generate a larger amount of VMT, due to longer commuting distances and the vehicle relocation process. To obtain more robust transportation costs in the era of SAVs, trip assignment module should be included in the model. Finally, the model assumes that residential location preferences, i.e., the coefficients, and market development patterns will not change over time. More scenario analyses can be conducted to explore residential location choices given preference variations (i.e., change in demand) in the future. This model can also be integrated with real-estate market development model to explore how changes in zoning ordinance and land use regulations may lead to variations in new property development (i.e., supply change), and correspondingly the residential location choices.

REFERENCE

AAA. 2010. “Your Driving Cost: How Much Are You Really Paying to Drive? (2010 Edition).” http://exchange.aaa.com/wp-content/uploads/2012/04/201048935480.Driving-Costs-2010.pdf.

———. 2016. “Your Driving Cost: How Much Are You Really Paying to Drive? (2016 Edition).” http://exchange.aaa.com/wp-content/uploads/2016/04/2016-YDC-Brochure.pdf.

Albright, Jerry, Alex Bell, Joe Schneider, and Chris Nyce. 2016. “Marketplace of Change: Automobile Insurance in the Era of Autonomous Vehicles.” KPMG.

Alonso, William. 1964. “Location and Land Use. Toward a General Theory of Land Rent.” *Location and Land Use. Toward a General Theory of Land Rent.*

Bansal, Prateek, and Kara M. Kockelman. 2016. “Are We Ready to Embrace Connected and Self-Driving Vehicles? A Case Study of Texans.” *Transportation*, 1–35.

Bansal, Prateek, Kara M. Kockelman, and Amit Singh. 2016. “Assessing Public Opinions of and Interest in New Vehicle Technologies: An Austin Perspective.” *Transportation Research Part C: Emerging Technologies* 67: 1–14.

Barclays. 2016. “Disruptive Mobility: A Scenario for 2040.” Barclays Research.

Ben-Akiva, Moshe E., and Steven R. Lerman. 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*. Vol. 9. MIT press.

Bridges, Rutt. 2015. *Driverless Car Revolution: Buy Mobility, Not Metal*. Amerzon.com.

Burns, Lawrence D., William C. Jordan, and Bonnie A. Scarborough. 2013. “Transforming Personal Mobility.” *Earth Island Institute, Columbia University*.

CityMobil2 Project. 2016. “CityMobil2 Project Management Committee Selected 3 Large-Scale Demonstration Sites,” 2016. http://www.citymobil2.eu/en/City-activities/Large-Scale-Demonstration/Overview/.

Coyne, Justine. 2015. “Here’s Your First Look at Uber’s Test Car.” Pittsburgh Business Times. May 22, 2015. http://www.bizjournals.com/pittsburgh/blog/techflash/2015/05/exclusive-heres-your-first-look-at-ubers-self.html.

Croissant, Yves. 2010. *Mlogit: Multinomial Logit Model*. R package version 0.1-5, URL http://CRAN. R-project. org/package= mlogit.

Curtis, Sophie. 2016. “First Self-Driving ‘pod’ Unleashed on Britain’s Streets,” 2016. http://www.telegraph.co.uk/technology/news/11866132/First-self-driving-pod-unleashed-on-Britains-roads.html.

Fagnant, Daniel J., and Kara M. Kockelman. 2014. “The Travel and Environmental Implications of Shared Autonomous Vehicles, Using Agent-Based Model Scenarios.” *Transportation Research Part C: Emerging Technologies* 40: 1–13.

———. 2015. “Dynamic Ride-Sharing and Optimal Fleet Sizing for a System of Shared Autonomous Vehicles.” In *Transportation Research Board 94th Annual Meeting*.

Fagnant, Daniel J., Kara M. Kockelman, and Prateek Bansal. 2015. “Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market.” *Transportation Research Record: Journal of the Transportation Research Board*, no. 2536: 98–106.

Greenblatt, Jeffery B., and Samveg Saxena. 2015. “Autonomous Taxis Could Greatly Reduce Greenhouse-Gas Emissions of US Light-Duty Vehicles.” *Nature Climate Change*.

Guo, Jessica Y., and Chandra R. Bhat. 2007. “Operationalizing the Concept of Neighborhood: Application to Residential Location Choice Analysis.” *Journal of Transport Geography* 15 (1): 31–45.

Habib, Khandker Nurul, and Kara Kockelman. 2008. “Modeling Choice of Residential Location and Home Type: Recent Movers in Austin Texas.” In *87th Annual Meeting of the Transportation Research Board, Washington, DC*.

Habib, Muhammad, and Eric Miller. 2009. “Reference-Dependent Residential Location Choice Model within a Relocation Context.” *Transportation Research Record: Journal of the Transportation Research Board*, no. 2133: 92–99.

Hawkins, Andrew J. 2017. “Apple Just Received a Permit to Test Self-Driving Cars in California.” The Verge. April 14, 2017. https://www.theverge.com/2017/4/14/15303338/apple-autonomous-vehicle-testing-permit-california.

Krueger, Rico, Taha H. Rashidi, and John M. Rose. 2016a. “Adoption of Shared Autonomous Vehicles--A Hybrid Choice Modeling Approach Based on a Stated-Choice Survey.” In *Transportation Research Board 95th Annual Meeting*.

———. 2016b. “Preferences for Shared Autonomous Vehicles.” *Transportation Research Part C: Emerging Technologies* 69: 343–55.

Lee, Brian HY, Paul Waddell, Liming Wang, and Ram M. Pendyala. 2010. “Reexamining the Influence of Work and Nonwork Accessibility on Residential Location Choices with a Microanalytic Framework.” *Environment and Planning A* 42 (4): 913–30.

Litman, Todd. 2014. “Autonomous Vehicle Implementation Predictions.” *Victoria Transport Policy Institute* 28.

Martinez, Luis M., Gonçalo HA Correia, and José M. Viegas. 2015. “An Agent-based Simulation Model to Assess the Impacts of Introducing a Shared-taxi System: An Application to Lisbon (Portugal).” *Journal of Advanced Transportation* 49 (3): 475–95.

McFadden, Daniel. 1978. “Modeling the Choice of Residential Location.” *Transportation Research Record*, no. 673.

NuTonomy. 2016. “NuTonomy and Grab Launch Partnership to Expand Public Trial of On-Demand Self-Driving Car Service in Singapore,” 2016. http://nutonomy.com/press.html.

Palma, André de, Nathalie Picard, and Paul Waddell. 2007. “Discrete Choice Models with Capacity Constraints: An Empirical Analysis of the Housing Market of the Greater Paris Region.” *Journal of Urban Economics* 62 (2): 204–30.

Pinjari, Abdul Rawoof, Chandra R. Bhat, and David A. Hensher. 2009. “Residential Self-Selection Effects in an Activity Time-Use Behavior Model.” *Transportation Research Part B: Methodological* 43 (7): 729–48.

Pinjari, Abdul Rawoof, Ram M. Pendyala, Chandra R. Bhat, and Paul A. Waddell. 2011. “Modeling the Choice Continuum: An Integrated Model of Residential Location, Auto Ownership, Bicycle Ownership, and Commute Tour Mode Choice Decisions.” *Transportation* 38 (6): 933–58.

Rigole, Pierre-Jean. 2014. “Study of a Shared Autonomous Vehicles Based Mobility Solution in Stockholm.”

Schirmer, Patrick M., Michael AB van Eggermond, and Kay W. Axhausen. 2014. “The Role of Location in Residential Location Choice Models: A Review of Literature.” *Journal of Transport and Land Use* 7 (2): 3–21.

Shen, Wen, and Cristina Lopes. 2015. "Managing Autonomous Mobility on Demand Systems for Better Passenger Experience." In *PRIMA 2015: Principles and Practice of Multi-Agent Systems*, 20–35. Springer.
Shen, Yu, Hongmou Zhang, and Jinhua Zhao. 2017. "Embedding Autonomous Vehicle Sharing in Public Transit System: An Example of Last-Mile Problem."
Spieser, Kevin, Kyle Treleaven, Rick Zhang, Emilio Frazzoli, Daniel Morton, and Marco Pavone. 2014. "Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore." In *Road Vehicle Automation*, 229–45. Springer.
Thünen, Johann Heinrich von. 1826. "Der Isolierte Staat in Beziehung Auf Nationalökonomie Und Landwirtschaft." *Gustav Fischer, Stuttgart (Reprinted 1966)*.
U.S. Department of Transportation. 2016. "Secretary Foxx Unveils President Obama's FY17 Budget Proposal of Nearly $4 Billion for Automated Vehicles and Announces DOT Initiatives to Accelerate Vehicle Safety Innovations | National Highway Traffic Safety Administration (NHTSA)." 2016. http://www.nhtsa.gov/About+NHTSA/Press+Releases/dot-initiatives-accelerating-vehicle-safety-innovations-01142016.
Waddell, Paul. 2002. "UrbanSim: Modeling Urban Development for Land Use, Transportation, and Environmental Planning." *Journal of the American Planning Association* 68 (3): 297–314.
Waddell, Paul, Gudmundur F. Ulfarsson, Joel P. Franklin, and John Lobb. 2007. "Incorporating Land Use in Metropolitan Transportation Planning." *Transportation Research Part A: Policy and Practice* 41 (5): 382–410.
Zhang, Wenwen, and Subhrajit Guhathakurta. 2017. "Parking Spaces in the Age of Shared Autonomous Vehicles: How Much Parking Will We Need and Where?" *Transportation Research Record: Journal of the Transportation Research Board*, no. 2651: 80–91.
Zhang, Wenwen, Subhrajit Guhathakurta, Jinqi Fang, and Ge Zhang. 2015a. "Exploring the Impact of Shared Autonomous Vehicles on Urban Parking Demand: An Agent-Based Simulation Approach." *Sustainable Cities and Society* 19: 34–45.
———. 2015b. "The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach." In *Transportation Research Board 94th Annual Meeting Proceeding*.
Zhang, Wenwen, Subhrajit Guhathakurta, and Elias B. Khalil. 2018. "The Impact of Private Autonomous Vehicles on Vehicle Ownership and Unoccupied VMT Generation." In *Transportation Research Board 98th Annual Meeting Proceeding*.
Zhou, Bin, and Kara Kockelman. 2008. "Microsimulation of Residential Land Development and Household Location Choices: Bidding for Land in Austin, Texas." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2077: 106–12.