HOW DO LAND USE PATTERNS AFFECT OWNERSHIP AND USE OF SELF-DRIVING VEHICLES?

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Accepted for presentation at the 98th Meeting of the Transportation Research Board and publication in *Transportation Research Record*.

ABSTRACT

Connected and automated (self-driving) vehicles (CAVs and AVs) will soon become a viable mode option. Past work has shown the rate at which AVs are implemented depends on several factors, such as individual and household demographics and technology costs. This research analyzes another group of attributes that help predict the adoption of new vehicle technologies: land use characteristics.

Here, the results of two large-scale preference surveys are used to estimate how land use characteristics impact Americans' perceptions of, interest in, and willingness to pay for AV technology, while controlling for demographic attributes. Both surveys were conducted in 2017 and together represented over 4,000 U.S. households.

Statistical models like the ordered probit and multinomial logit are used to estimate the impacts of demographics and land use characteristics on AV-related behavior. Diversity of land uses in a neighborhood and the quality of access to destinations for households in that neighborhood are the most significant predictors of one's expected use of AVs. Namely, a poor mix of land uses and limited access to key destinations are associated with higher levels of interest in AVs, higher anticipated use of AV technology, higher likelihood of utilizing DRS, and increased willingness-to-pay (WTP) for self-driving capability.

This research provides metrics of practical (not just statistical) significance of a suite of land use variables, relative to common demographic predictors, to identify for planners, engineers, policymakers, and others where AV deployments may go fastest, first.

BACKGROUND

The relationship between land use and transportation is inter-related and complex. One's environment informs his or her transportation decisions and vice versa.

The purpose of this analysis is to predict how self-driving vehicle technology may be used and acquired in the future. Such a complex and advanced form of technology is already garnering interest from large segments of the population. Anticipating who may adopt this technology, how much they are willing to pay for it, and how their travel behavior may change as a result is of keen interest to those parties mentioned previously, but also firms and manufacturers in the business of transportation.

Density, diversity of land uses, urban design, destination accessibility, and distance to transit comprise a set of land use variables commonly referred to as the “5D’s” of development. Their prevalence (or lack thereof) in a neighborhood has been shown to inform one’s transportation decisions. For example, households located in regions with high job density and a good mix of land uses tend to produce less vehicle-miles traveled (VMT) than those in areas which are exclusively residential. Since urban form dictates travel patterns, it is likely those same built environment characteristics affect interest in and perception of new vehicle technology as well.

Examples of land use influencing transportation decisions have been investigated previously. For example, Zhang (2004) found characteristics like density and diversity of land uses were influential in predicting one’s mode choice. It stands to reason that the same variables could be used to predict one’s use of self-driving vehicle technology.

The Use of Self-Driving Vehicles

The idea of a self-driving vehicle is not new. Visions of vehicles without a human driver have been the source of intrigue since the early days of the automobile (The Milwaukee Sentinel, 1926). More recent efforts are making what was once a dream into a reality. Established automobile manufactures like General Motors, and new market entrants like Waymo (a member of Google’s parent company, Alphabet) are racing to bring AVs to consumers (Navigant Research, 2018). Opinions vary on how soon this technology will penetrate the market. Bansal and Kockelman (2017) suggest fully automated vehicles could have anywhere from 25 to more than 80% market share by 2045. Recognizing such an introduction is no far-off fantasy, the last decade has seen a concerted effort by researchers and practitioners to predict and plan for the rise of the self-driving vehicle.

A wrinkle in the world of AVs is the idea of shared automated vehicles (SAVs). This transportation mode operates like contemporary transportation network companies (TNCs), such as Lyft and Uber, by providing on-demand travel services, but without the presence of a driver. Fagnant and Kockelman (2016) found that one SAV may be able to substitute for approximately 10 privately-owned vehicles when they modeled a fleet in the Austin, Texas market. That being said, the model used in this research limited it analysis region to a 12 by 24-mile area. In doing so, many household trips were not accounted for. A later study by Liu et al. (2017) expanded the area of interest to the entire Capital Area Metropolitan Planning Organization’s (CAMPO) 6-county region, accounting for approximately 8.8 million person-trips. They found that by pricing SAVs at $1 to $1.25 per mile, each SAV could replace 7.7 privately-owned human driven vehicles. Loeb et al. (2018) furthered this research by considering electric SAVs (SAEVs) on the 6-county network. With average wait times near 7 minutes, one SAEV could serve 7 passengers. Wait times vary with charging time as well, ranging from 10.1 to 4.4 minutes at 4-hour and 30-minute charge times, respectively.

Dynamic ride-sharing (DRS) is a method already being employed by TNCs (i.e., Uber Pool and Lyft Line) wherein passengers share a portion of their vehicle and trip with strangers headed in the same general direction. DRS will also likely be employed on SAVs to maximize the number of service a single vehicle can provide and limit empty or single-occupant vehicles.

Self-Driving Vehicles and Land Use

Past work has been aimed at predicting how transportation and land use relationship will be affected by AVs. It is possible the lower cost of driving will lead to further VMT increases and sprawl (Fagnant and Kockelman, 2015). Those with longer commutes tend to be more likely to adopt SAVs, potentially increasing overall VMT as empty vehicles roam empty waiting for passengers (Haboucha et al., 2017).

Meyer et al. (2017) found that introduction of AVs in exclusively exurban areas (characterized by limited access highways) increased accessibility between 10 and 14%. Accessibility calculates the connectedness of an activity to the transportation system by weighting opportunities with costs. In the case of widespread, private AV use, much of the "positive" gains in accessibility were offset by the "negative" of increased travel demand due to empty trips. Meyer et al. (2017, p. 90) note "well-connected rural municipalities experience the strongest increase in accessibility, whilst the effect in city centers is much less strong or even negative." Such a result indicates households may become more interested in locating far from the urban core. The work here seeks to understand whether AVs will be more in demand by households already far from the urban core or perhaps those wishing to relocate there.

Measuring Land Use Variables

The connection between land use and transportation and land use has been widely studied. Meta-analyses by Ewing and Cervero (2001 & 2010) and Stevens (2017) investigated the effects of the "5D's" on vehicle-miles traveled (VMT). They found destination accessibility and design of the transportation network to be the most important factors in determining the amount of travel one partakes in. Stevens (2017) also identified job accessibility and population density as important indicators of VMT. A notable conclusion drawn from this research was that impacts were location specific and often inter-related, no matter the variable in question. For example, it is unlikely to find a dense development with only a single land use type. Past work shows how CAV technology is intertwined with land use. The work here looks at the land use and transportation relationship from another angle. It is particularly interested in how the built environment characteristics of one's neighborhoods informs his or her interest in new vehicle technologies.

SURVEY DATA

The stated preferences expressed in these results come from two nationwide surveys. The first, from Quarles and Kockelman (2018) focused on consumer interest and WTP for AV technology and electric vehicles. In addition to demographic data from the survey, location data provided by survey respondents were attributed to land use data from the EPA's Smart Location Database (SLD).

An early first step was to "clean" the survey data for any contradictory or nonsensical responses. Part of this process involved ensuring all respondents gave location data. After removing those households who did not provide their location, 1,423 responses remained.

The second survey was similarly interested in new vehicle technologies and consumers' willingness to pay for them, but also posed questions related to ethics and long-distance travel Gurumurthy and Kockelman (2018). Households across the United States were surveyed and a cleaning process similar to that discussed above resulted in 2,588 responses.

One should approach these results with a degree of caution. Because AV technology is perceived as futuristic and inaccessible to most, the responses given in choice experiments may not be entirely accurate (Krueger et al., 2016; Bansal and Kockelman, 2017). People are fascinated by the idea of self-driving vehicles even if they are not yet ready to adopt the technology or trust it yet (Kyriakidis et al., 2015). While some show great enthusiasm for AV technology, a large percentage of the population have concerns related to safety, legal issues and cost.

Population Weighting

No survey can be expected to capture a perfect sample of the population. To best represent preferences across the country, population weighting was applied to the responses. For example, in the first survey, women were over-sampled (i.e., they comprised 63% of survey responses, whereas only represent 51% of the U.S. population). In addition to gender, various other demographic attributes were used as benchmarks to weight each response. Based on weighting from the U.S. Census Public Use Microdata Sample (PUMS), an iterative process was used to bring the sample statistics as close as possible to actual conditions. Weights were applied at both the household and individual levels.

LAND USE DATA

The "5D" variables used for this analysis came from the SLD. Variables are presented in this database at the census block group level. Conversely, survey respondents gave their location at the zip code level. 5-digit zip codes were associated with census tracts via a relationship file provided by the United States Department of Housing and Urban Development (HUD)[1]. Census tracts and zip codes do not overlay perfectly, as zip codes are delineated in such a way as to minimize delivery time of mail whereas census tracts are drawn to capture approximately equal portions of the population. That being said, they are sufficiently linked so as to provide valuable urban form data. Since the land use variables in the SLD are at the block group level and location data was at the tract level, a weighted average of all block groups within a tract was taken for each variable. This population-based weighted average was tied to the results of the 2016 American Community Survey (ACS).

Density, the first of the "5Ds" is represented by housing, population, and job density. All three variables are measured in terms of units per unprotected acre (EPA, 2014). Protected lands are designated as such to conserve them, often for ecological reasons, and therefore are ineligible for development.

Measuring diversity of land uses is considerably more complicated than doing so for density. It would be an extremely arduous task to evaluate the exact land use of every parcel in every census block group in the United States. Instead, the developers of the SLD used existing data to make assumptions about each region of interest (EPA, 2014). For example, when looking at the balance between housing and jobs (a common measure of diversity of land uses), a simple ratio of housing

[1] https://www.huduser.gov/portal/datasets/usps_crosswalk.html

units to jobs within the entire block group was taken. As noted in the SLD User Guide, this is potentially problematic as such a ratio does not provide any insight into the spatial distribution of jobs and housing units within a block group. Another measure used to evaluate diversity is the ratio of trips departing a block group to those entering. An index, named trip equilibrium, uses trip generation values provided by the Institute of Transportation Engineering (ITE) Trip Generation Manual to calculate the number of vehicle trips created by households in a block group and the number of trips attracted there by the available employment opportunities (EPA, 2014). Finally, a regional diversity index was calculated by considering the total population and employment within a block group.

Design measures refer to the physical make-up of a region. For example, the measure of network density evaluates the number of transportation facility miles per acre within a block group (EPA, 2014). These facilities may be auto-focused, multi-modal or pedestrian-focused. Another design measure is intersection density. As the name implies, this is calculated by taking a weighted sum of all intersections within a block group. The weights are based on which facility types are intersecting. Notably, intersections which connected multiple auto-centric facilities were given a weight of zero because they often impede non-motor vehicle transportation modes. Due to this weighting, the intersection density variable can be used as somewhat of a proxy for “walk scores” or other similar pedestrian-focused land use variables. “Walk scores” can vary greatly across a zip code and therefore using it as an explanatory variable for this analysis was not feasible. Instead, through use of intersection density, the researchers have sought to understand how conditions for active transport (i.e., walking and cycling) may impact one’s adoption and use of AVs.

Evaluating the fourth “D” variable, distance to transit, can be tricky. For one, many regions in the United States lack access to transit in any form. Furthermore, even if transit is present, there is no guarantee the service provided by a nearby transit stop is reliable or efficient enough to serve as a viable mode alternative. For the purposes of this project, transit accessibility was measured by finding the shortest distance from the population center of a census block group to a transit stop (so long as it was less than 0.75 miles) (EPA, 2014).

Destination accessibility, the final of the “5D’s” was evaluated in two similar, yet distinct, ways. One variable looks at the number of jobs available within a 45-minute automobile trip. This was calculated by summing the jobs in all census block groups that had a centroid within a 45-minute automobile trip (EPA, 2014). The second measure is very similar. The only difference is that it sums job accessible within a 45-minute transit trip. As mentioned previously, this is not an option for all communities, a fact which is reflected in the data.

Some land use variables were directly asked. In survey by Quarles and Kockelman (2018), respondents were asked the approximate distance to the nearest transit stop, grocery store, their place of work or school, and downtown. The first is a “D” variable itself. The others examples of destination accessibility, each related to different trip purposes. For example, a trip to the grocery store is considered personal business, whereas a trip downtown may be for work or recreation.

Finally, the data for average household income by census block group was retrieved from the 2016 ACS.

SUMMARY STATISTICS

Most of the summary statistics in Table 1 come from the SLD. The first half covers land use variables associated with data from the survey by Quarles and Kockelman (2018) whereas the second is in reference to the survey by Gurumurthy and Kockelman (2018). Note the asterisked variables came directly from survey respondents and average household income is based on results from the 2016 ACS.

TABLE 1 Summary Statistics for Land Use Variables

n = 1,423 survey respondents					
"D" Variable of Interest	**Variable**	**Mean**	**Std. Dev.**	**Min**	**Max**
Density	Housing Units per Acre	3.42	12.30	0	233.44
	People per Acre	7.35	22.58	0	275.84
	Jobs per Acre	5.54	44.43	0	889.80
Diversity of Land Uses	Jobs per Household	72.23	847.77	0	20,619
	Trip Equilibrium	0.37	0.22	0	0.96
	Regional Diversity	0.18	0.18	0	0.99
Density	Road Network Density (facility miles/acre)	11.17	8.63	0.02	49.72
	Intersection Density (number of intersections per block group)	45.04	54.27	0	636.25
Distance to Transit	Distance to Transit (miles)	44.5	26.5	0	62.1 (constrained)
	Self-reported Distance to Nearest Transit Stop (miles)*	7.59	14.54	0	130.76
Destination Accessibility	Jobs within a 45min Automobile Trip	116,128	179,609	64.25	1,365,189
	Jobs within a 45min Transit Trip	6,571	27,944	0	356,152
	Self-reported Distance to Nearest Grocery Store (miles)*	5.01	7.67	0.03	103.48
	Self-reported Distance to Work or School (miles)*	7.92	13.97	0	179.45
	Self-reported Distance to Downtown (miles)*	10.22	14.32	0	156.58
	Average Household Income ($/year)+	78,799	44,310	0	437,929
n = 2,588 survey respondents					
"D" Variable of Interest	**Variable**	**Mean**	**Std. Dev.**	**Min**	**Max**
Density	Housing Units per Acre	2.27	7.53	0	233.44
	People per Acre	5.37	15.78	0	275.30
	Jobs per Acre	3.11	28.27	0	1,168
Diversity of Land Uses	Jobs per Household	112.79	1,019	0	20,619
	Trip Equilibrium	0.35	0.22	0	1.00
	Regional Diversity	0.18	0.18	0	0.99

Density	Road Network Density (facility miles/acre)	10.63	8.05	0.11	46.05
	Intersection Density (number of intersections per block group)	40.92	45.05	0	636.25
Distance to Transit	Distance to Transit (miles)	49.3	24.0	0	62.1 (constrained)
Destination Accessibility	Jobs within a 45min Automobile Trip	102,623	135,658	0	1,420,953
	Jobs within a 45min Transit Trip	3,850	18,571	0	359,681
	Average Household Income ($/year)+	78,798	45,051	0	447,880

*Question was asked directly of survey respondents
+Data from 2016 ACS
All other data comes from the EPA's Smart Location Database

Further summary statistics from the surveys used in this analysis can be found in work by Quarles and Kockelman (2018) and Gurumurthy and Kockelman (2018).

RESULTS

The focus of this paper is on the potential land use may have in influencing the adoption and use of self-driving vehicles. The analyses detailed in these results include demographic explanatory variables originating from the surveys of interest. For the sake of brevity and in the interest of a focused report, these variables will not be discussed in this paper. For more detailed investigation of these variables please refer to Quarles and Kockelman (2018) and Gurumurthy and Kockelman (2018).

In addition to presenting the statistical significance of each explanatory variable, practical significance is also given. This was calculated in one of two ways. For continuous variables, like density, the variable for each respondent in the dataset was increased by 1 standard deviation. This adjusted value was placed into the regression function (y) produced by the applicable model, which was then recalculated. For binary responses, like possession of a driver's license, all respondents were given a value of 1. That is to say, the practical significance measure the impact of the entire population becoming licensed drivers. For both methods, a population-weighted average of the resulting y-values was taken. The difference between this average and the unchanged one was normalized by dividing by the standard deviation (Equation 1).

$$\Delta \mathrm{Y\ w.r.t.\ SD} = \frac{\bar{y}_{changed} - \bar{y}_{unchanged}}{\sigma} \quad (1)$$

Interest in AVs

The first area of focus in understanding the adoption and expected behavioral patterns associated with self-driving vehicles is simply the interest one has in acquiring the technology. The results seen in Table 2 explore this question. Respondents were first asked their interest in owning or leasing a completely self-driving vehicle. They were given the opportunity to respond on a 4-point scale ranging from "not interested" to "very interested." Due to the nature of the question and the possible responses, an ordered probit model was used to determine the impact of explanatory variables on one's interest in an AV.

In terms of land use, some key results can be gleaned. The strongest predictor, as indicated by its practical significance, is job accessibility. This highlights the fact that those with existing access to career opportunities appear to see less of a need for automated vehicle technology. This is related to the significance of the trip equilibrium index. A neighborhood's higher mismatch of trip producers and attractors is shown as a potential boost to AV interest. Those who cannot walk to nearby diverse land uses may see AVs as more advantageous. The next strongest predictor is network density. A neighborhood with a higher concentration of transportation facilities is more likely to see households expressing interest in AVs. Housing density is also predictive of one's interest. Based on these findings, the denser the neighborhood, the more likely one is to show interest in ownership of a self-driving vehicle. The link between dense development and dense transportation networks is apparent to anyone who has visited a large city's downtown area. Finally, as one's access to transit decreases, their interest in AVs follows suit. It is possible that those used to using an alternate mode like transit are more inclined to explore the possibility of travel via AV.

The next piece of analysis investigates whether survey respondents identified a high number of benefits related to AVs, which may influence their adoption of the technology. Respondents could select any number of the following reasons for why they might see self-driving technology as beneficial: enhanced safety, congestion relief, the ability to partake in other activities instead of driving, the reliability of a self-driving car, its role as a convenient alternative to public transit due to the ability to be dropped off closer to one's destination, and the ability to self-park. If the respondents showed interest in at least three of these potential benefits, they were assigned a high level of interest in the benefits of self-driving technology. To analyze if a respondent showed such interest, a binomial logit model was used.

The results in Table 2 indicate those in areas with a good mix of land uses see the greatest benefit originating from self-driving vehicles. Both the trip equilibrium index and regional diversity index appear as significant predictors of this mindset. This may be because those living in neighborhoods with diverse land uses see the benefit in advances like congestion management, transit alternatives, and self-parking. AVs have the potential to de-clog crowded streets, deliver one to their doorstep instead of a transit stop a few blocks away, and eliminate the need to "cruise" for parking. At first glance it may appear the two measures of land use diversity are at odds. In fact, they are telling the same story. A higher value in the regional diversity index indicates a good mix of land uses, whereas a trip equilibrium index close to 1 is associated with the same conditions. This is because a good mix of land uses can be expected to produce and attract approximately the same number of trips.

Respondents identifying at least three areas of concern were labeled as expressing high levels of trepidation towards AV technology. Respondents could indicate their concern regarding the (yet unproven) safety benefits provided by self-driving cars, faulty software in self-driving cars, the mixture of human-driven and self-driven cars, the decreased privacy in a self-driving car, or the possibility of being tracked in a self-driving car. For the same reasons indicated in the previous analysis, a binomial logit model was used for this regression.

Here the only land use variable of significance is density. As the number of people in a given area increase, the concern towards AVs decreases. This may be because those in denser urban areas tend to be more tech-savvy. Many of the concerns associated with AVs are similar to those associated with any new innovation. This is at odds with housing density, which tells the opposite story. As the number of housing units per acre increase, the likelihood one expresses high levels of concerns regarding self-driving vehicles also increases. A possible root of this discrepancy is that housing density accounts for all housing, regardless of occupancy and therefore includes vacant dwellings in its count.

TABLE 2 Model Estimation Results for Self-Driving Vehicle Interest

Interest in owning or leasing a completely self-driving vehicle? (*n* = 1,422)			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Housing Units Per Acre	0.005	0.185	+6.4%
Trip Equilibrium Index	0.285	0.033	+6.4%
Network Density	1.69E-02	0.000	+15.0%
Distance to Transit	-1.39E-06	0.094	-6.2%
Jobs within a 45min Transit Trip	-2.71E-06	0.120	-50.2%
Is Not Disabled?	-0.235	0.035	**Y**: -1.6%
Household Size	0.082	0.013	+11.1%
Age of Respondent (in years)	-0.014	0.000	-21.8%
Is Male?	0.329	0.000	+19.7%
Possess a U.S. Driver's License?	0.455	0.001	**Y**: +2.7%
Is Caucasian?	-1.68E-01	0.030	**Y**: -4.6%
Number of Children in Household	0.080	0.103	+7.7%
Household Income	2.36E-06	0.001	+11.7%
Possess a College Degree?	0.090	0.164	**Y**: +4.9%
Is Employed?	0.157	0.015	**Y**: +7.3%
	Coeff.	**Std Error**	
Ψ_1	0	[constrained]	
Ψ_2	0.676	0.033	
Ψ_3	1.408	0.045	
McFadden's R-Square: 0.108 **McFadden's adjusted R-Square**: 0.101			

Does the respondent identify a high number of benefits related to AVs? (*n* = 2,588)			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	0.385	0.074	
Trip Equilibrium Index	-0.381	0.057	-11.0%
Regional Diversity Index	0.706	0.005	+16.2%
Is Male?	-0.220	0.006	**Y**: +14.8%
Possess U.S. Driver's License?	-0.421	0.011	**Y**: -5.7%
Household Income	1.55E-06	0.074	+9.5%
Is a Student?	0.340	0.059	**Y**: +41.1%
Pseudo R-Square: 0.008		**Likelihood Ratio Chi-Square**: 28.35	
Does the respondent identify a high number of concerns related to AVs?			

(*n* = 2,588)			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	-0.784	0.002	
Housing Units per Acre	0.020	0.197	+17.4%
People per Acre	-0.013	0.101	-24.0%
Age of Respondent	0.004	0.156	+7.4%
Is Male?	0.137	0.092	**Y**: -8.0%
Possess a U.S. Driver's License?	0.327	0.057	**Y**: +3.8%
Is Caucasian?	0.151	0.138	**Y**: +6.5%
Possess a College Degree?	-0.138	0.097	**Y**: -10.1%
Is Employed?	-0.201	0.022	**Y**: -10.8%
Pseudo R-Square: 0.009	**Likelihood Ratio Chi-Square**: 32.58		

Autonomous Vehicle Usage

Another key area of interest related to AV technology is how much self-driving vehicle owners expect to use the technology available to them. Respondents were asked to predict the percentage of time they anticipated having their vehicle in self-driving mode (assuming the option was available to them). Because not all respondents indicated an interest in having a self-driving option on their vehicle in the first place, a hurdle model was used. The selection model first evaluates whether a respondent will put their vehicle in self-driving mode more than 0% of the time, then using an exponential regression model, those respondents with a non-zero response are evaluated to predict their percentage of time spent in the mode.

The results of this analysis are shown in Table 3. A number of land use variables arise as significant. Three variables related to destination accessibility (distance to the nearest grocery store, work or school, and downtown) are the strongest and indicate that those living further from such important destinations expect to use their AV technology more frequently. Dense development is also associated with a higher amount of expected time spent in self-driving mode. Perhaps this is because those living in denser areas are more used to traffic congestion and hope to enjoy the ability to partake in other activities instead of driving once the technology becomes available. Finally, similar to the results found when investigating interest in AVs, those living in areas with a poorer mix of land uses expect to utilize AVs more frequently.

A hurdle model is also used to predict one's expected use of dynamic ride-sharing (DRS). Those respondents expressing at least some interest in using DRS are evaluated using the exponential regression model.

Here as well, those living in a neighborhood with a poor mix of land uses anticipate utilizing DRS more frequently than those with a rich one. Living further from one's destination is correlated with a higher likelihood of using DRS. These results are not extremely surprising but they do highlight a potentially important result. There appears to be a connection between those willing to use DRS and those willing to pay more for (and show interest in) self-driving vehicle technology. This is potentially advantageous because if AV users can be encouraged to complete a considerable portion of their trips via DRS, there is potential for decreasing the number of vehicles on the road, therefore mitigating the possible higher degrees of congestion expected as driving becomes easier with AVs.

TABLE 3 Model Estimation Results for Predicting Self-Driving Technology Usage

Expected Percentage of Time Spent in Self-Driving Mode (*n* = 1,422)			
Exponential Regression Model			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	4.614	0.000	
Housing Units per Acre	0.005	0.164	+1.3%
Trip Equilibrium Index	0.496	0.019	+2.4%
Regional Diversity Index	-5.07E-01	0.046	-2.0%
Distance to Nearest Grocery Store	0.014	0.026	+2.4%
Distance to Work or School	0.009	0.011	+2.9%
Distance to Downtown	0.019	0.000	+6.0%
Household Size	-0.228	0.000	-6.7%
Age of Respondent (in years)	-0.025	0.000	-8.5%
Is Male?	7.32E-01	0.000	**Y**: +9.6%
Is Caucasian?	-1.360	0.000	**Y**: -7.4%
Household Income	5.87E-06	0.000	+6.2%
Possess a College Degree?	-1.065	0.000	**Y**: -12.0%
Is Married?	0.173	0.084	**Y**: +1.8%
Selection Model			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	1.929	0.000	
Jobs per Household	-7.06E-05	0.089	-3.1%
Age of Respondent (in years)	-0.009	0.007	-7.3%
Is Caucasian?	-0.509	0.001	**Y**: -7.8%
Children in Household	0.086	0.149	+4.2%
Possess a College Degree?	0.270	0.003	**Y**: +7.8%
Pseudo R-Square: 0.053	**Likelihood Ratio Chi-Square**: 512.99		
Expected Percent of Travel Completed via Dynamic Ride-Sharing assuming a 40% Discount on Shared Autonomous Vehicle Fares (n = 1,422)			
Exponential Regression Model			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	3.501	0.000	
Trip Equilibrium Index	0.476	0.039	+2.5%
Distance to Nearest Grocery Store	0.024	0.002	+4.6%
Distance to Work or School	0.012	0.006	+4.0%
Distance to Downtown	0.015	0.001	+5.1%
Average Household Income	1.54E-06	0.176	+1.7%
Household Size	-0.338	0.000	-10.8%

Age of Respondent (in years)	-0.034	0.000	-12.9%
Is Male?	0.964	0.000	**Y**: +13.7%
Possess a U.S. Driver's License?	0.547	0.019	**Y**: +0.8%
Is Caucasian?	-1.372	0.000	**Y**: -8.6%
Children in Household	0.190	0.024	+4.3%
Household Income	5.85E-06	0.000	+6.8%
Possess a College Degree?	-9.95E-01	0.000	**Y**: -12.5%
Is a Student?	0.780	0.009	**Y**: +18.2%
Selection Model			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	1.704	0.000	
Jobs per Household	-6.2E-05	0.148	-5.2%
Distance to Transit	1.98E-06	0.086	+8.3%
Number of Jobs within a 45min Auto Trip	9.33E-07	0.009	+16.5%
Is Not Disabled?	-0.461	0.008	**Y**: -3.0%
Workers in Household	0.147	0.001	+13.8%
Age of Respondent (in years)	-0.010	0.000	-15.7%
Is Caucasian?	-0.248	0.026	**Y**: -6.2%
Pseudo R-Square: 0.073	**Likelihood Ratio Chi-Square**: 523.00		

Willingness-to-Pay

In exploring one's WTP for self-driving capabilities to be added onto a new vehicle, a hurdle model was used for similar reasons to those described previously. As some respondents indicated no desire to pay a premium of any kind for this technology, the selection model first evaluates those expressing an interest in paying a non-zero premium. From there, the exponential regression model seeks to understand what may predict the value of said premium.

The density variables in this analysis are at odds. The results indicate those living in neighborhoods with a high concentration of housing stock will pay more for self-driving technology whereas those living in areas with a high concentration of people will pay progressively less. This discrepancy may be due to the housing vacancy issue discussed prior to Table 2. As with previous results, those in more monotonous developments express greater interest in AVs (this time in the form of greater interest in paying for the technology). A higher number of jobs within reach of a neighborhood is associated with a higher willingness to pay for self-driving technology. It is possible the higher number of accessible opportunities gives one the ability to seek out a better-paying job and therefore gain more income to spend on the technology. Notably, the demographic explanatory variable of household income possesses a positive correlation with the same willingness to pay response variable. Also similar to the previous result, as distance to key destinations like work, school, or the downtown area increase, one's willingness to pay for self-driving capabilities follows suit. Those with longer travel times to their destinations likely see the advantage (and therefore place a higher value) on the benefits afforded by the ability to partake in activities other than driving.

TABLE 4 Model Estimation Results for WTP for Self-Driving Vehicle Technology

Willingness to Pay for Full Self-Driving Capabilities (*n* = 1,422)			
Exponential Regression Model			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	8.139	0.000	
Housing Units per Acre	0.016	0.091	+3.0%
People per Acre	-0.010	0.054	-3.4%
Trip Equilibrium Index	0.253	0.177	+0.8%
Jobs Within a 45min Auto Trip	4.22E-07	0.147	+1.1%
Distance to Work or School	8.96E-03	0.010	+1.9%
Distance to Downtown	0.019	0.000	+4.1%
Household Size	-0.118	0.015	-2.3%
Age of Respondent (in years)	-0.021	0.000	-5.0%
Is Caucasian?	-0.266	0.012	**Y**: -0.4%
Children in Household	0.131	0.049	+1.8%
Household Income	3.94E-06	0.000	+2.8%
Selection Model			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	2.313	0.000	
Jobs per Household	-6.1E-05	0.152	-2.6%
Network Density	0.014	0.009	+6.3%
Distance to Transit	-0.004	0.134	-2.9%
Average Household Income	-1.87E-06	0.041	-4.2%
Is Not Disabled?	-0.531	0.011	**Y**: -0.0%
Age of Respondent (in years)	-0.014	0.000	-11.1%
Is Caucasian?	-0.185	0.149	**Y**: -2.6%
Possess a College Degree?	0.180	0.035	**Y**: +4.9%
Pseudo R-Square: 0.12	**Likelihood Ratio Chi-Square**: 254.08		

Long-Distance Travel

The next set of analyses look at how respondents expect to conduct their long-distance travel in the presence of self-driving vehicles. The base case is existing modes of transportation (i.e. cars, buses, trains, and airplanes). A multinomial logit model was used to investigate whether respondents would instead show interest in self-driving vehicle options for their long-distance travel. Respondents were asked about their preferences for trips of three distances (50-100, 100-500, and 500+ miles). Further, for each of the distances, they were asked about their expected choices for vacation or recreational, personal, and business travel.

First, for the lowest length of travel, one’s access to transit diminished the expected use of a personal AV for recreational travel. Conversely, a high number of jobs in relative close proximity has the opposite effect. Similar to previous analyses, the high number of nearby jobs may indicate a higher amount of income to spend on a self-driving car. For personal travel (e.g. shopping), this access to jobs variable is similarly statistically significant. There were no land use variables which were statistically significant when it came to predicting one's use of an SAV for recreational or personal travel at this distance, nor for predicting one's business travel through a shared mode or otherwise.

At the next level of distance traveled, job accessibility remains a significant predictor for recreational or vacation travel via AV, likely for the same reasons discussed above. With regards to shared vehicle travel, the opposite is true. As job access opportunities diminish, the likelihood of using an SAV increases. Perhaps the decreased access to career opportunities can be associated with a desire to cut costs by sharing rides. In terms of personal travel, intersection density becomes slightly significant, indicating living in a more walkable community leads to a higher desire to use a personal AV for this form of long-distance travel. Intersection density moves in the opposite direction for shared vehicles. A less walkable neighborhood is associated with higher interest in sharing trips, perhaps because of the limited alternative modal options at one's disposal. For business trips at this distance, access to transit appears as statistically significant. Somewhat counter-intuitively, as one's distance from transit increases, interest in using a personal AV for long-distance travel decreases. Perhaps, these households are used to driving their own vehicle for long-trips (due to a lack of transit options) and do not see as much of a need for AV travel. For shared vehicle travel, density appears as statistically significant. This may be because denser development could result in decreased wait times for SAV pick-up. Also, similar to the case of vacation and recreation travel, a higher number of jobs within reach of one's location diminishes the likelihood of selecting SAV for travel.

Finally, for very long-distance travel (500+ miles), some important indicators arise as significant. For vacation/recreation travel, the model predicts higher levels of jobs in a neighborhood to be associated with a higher likelihood of selecting the private AV travel mode. For both personal and business travel, distance to transit and job accessibility are key explanatory variables. As one's distance from transit decreases, their likelihood of using a personal AV increases. These align with findings for other distances. Job accessibility is significant for all trip purposes, likely due to the same reasons discussed previously.

TABLE 5 Model Estimation Results for Long-Distance Travel

Mode Choice for Long-Distance *Vacation/Recreation* Travel of 50-100 miles				**Mode Choice for Long-Distance *Personal* Travel of 50-100 miles**			
n = 2,588							
Personal AV							
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	-0.790	0.049		Constant	-0.528	0.072	
Distance to Transit	-2.36E-06	0.198	-2.8%	Number of Jobs within a 45min Auto Trip	1.35E-06	0.001	+6.5%
Number of Jobs within a 45min Auto Trip	1.59E-06	0.002	+6.7%	Age of Respondent (in years)	0.019	0.000	+11.3%
Age of Respondent (in years)	0.018	0	+9.0%	Possess a U.S. Driver’s License?	-0.498	0.022	**Y**: -1.8%
Is Male?	0.165	0.16	**Y**: -2.6%	Is Caucasian?	-0.522	0.000	**Y**: -7.0%
Possess a U.S. Driver’s License?	-0.617	0.004	**Y**: -2.0%	Household Income	-4.15E-06	0.004	-7.0%
Is Caucasian?	-0.502	0.001	**Y**: -5.8%	Possess a College Degree?	-0.243	0.003	**Y**: -8.2%
Household Income	-5.58E-06	0	-8.1%	Is Employed?	-0.525	0.001	**Y**: -5.9%
Possess a College Degree?	-0.243	0.043	**Y**: -4.9%	Is a Student?	-0.869	0.019	**Y**: -28.6%
Is Employed?	-0.522	0.001	**Y**: -7.6%	Is Retired?	-0.340	0.072	**Y**: -9.8%
Is a Student?	-0.928	0.012	**Y**: -26.5%				
Is Retired?	-0.327	0.072	**Y**: -8.1%				
Shared AV							
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	0.701	0.034		Constant	0.355	0.149	
Age of Respondent (in years)	-0.023	0	-30.2%	Age of Respondent (in years)	-0.017	0.000	-26.5 %
Is Caucasian?	-0.260	0.024	**Y**: -7.8%	Household Income	2.08E-06	0.036	+9.4%
Household Income	1.89E-06	0.059	+7.1%	Possess a College Degree?	0.165	0.087	**Y**: +10.3%
Possess a College Degree?	0.126	0.193	**Y**: +6.5%				
Is Retired?	0.368	0.024	**Y**: +23.6%				
Pseudo R-Square: 0.041 **Likelihood Ratio Chi-Square**: 215.10				**Pseudo R-Square**: 0.035 **Likelihood Ratio Chi-Square**: 186.75			

Mode Choice for Long-Distance *Vacation/Recreation* Travel of 100-500 miles				**Mode Choice for Long-Distance *Personal* Travel of 100-500 miles**				**Mode Choice for Long-Distance *Business* Travel of 100-500 miles**			
n = 2,588											
Personal AV											
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	-0.943	0.008		Constant	-0.788	0.028		Constant	-0.578	0.072	
Number of Jobs within a 45min Auto Trip	8.45E-07	0.028	+3.2%	Intersection Density	0.002	0.136	+2.1%	Distance to Transit	-2.43E-06	0.124	-2.7%
Age of Respondent (in years)	0.021	0.000	+9.9%	Age of Respondent (in years)	0.019	0.000	+8.3%	Age of Respondent (in years)	0.025	0.000	+11.7%
Is Male?	0.274	0.018	**Y**: -4.0%	Possess a U.S. Driver's License?	-0.552	0.009	**Y**: -1.5%	Is Male?	0.407	0.000	**Y**: -6.0%
Possess a U.S. Driver's License?	-0.563	0.007	**Y**: -1.6%	Is Caucasian?	-0.487	0.000	**Y**: -4.9%	Children in Household	-0.096	0.067	**Y**: -2.7%
Is Caucasian?	-0.447	0.002	**Y**: -4.8%	Household Income	-4.52E-06	0.002	-5.7%	Household Income	-3.04E-06	0.006	-4.1%
Household Income	-6.42E-06	0.000	-8.5%	Possess a College Degree?	-0.380	0.001	**Y**: -6.6%	Possess a College Degree?	-0.352	0.001	**Y**: -6.5%
Possess a College Degree?	-0.317	0.007	**Y**: -5.8%	Is Employed?	-0.462	0.002	**Y**: -5.8%	Is Employed?	-1.106	0.000	**Y**: -15.0%
Is Employed?	-0.536	0.000	**Y**: -7.2%	Is a Student?	-0.649	0.109	**Y**: -16.1%	Is a Student?	-0.517	0.023	**Y**: -13.7%
Is a Student?	-0.716	0.032	**Y**: -18.7%	Is Retired?	-0.289	0.028	**Y**: -6.2%	Is Retired?	0.739	0.07	**Y**: +17.1%
Is Retired?	-0.433	0.016	**Y**: -9.9%								
Shared AV											
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	0.184	0.551		Constant	0.446	0.146		Constant	-0.368	0.404	
Number of Jobs within a 45min Auto Trip	-8.78E-07	0.023	-6.1%	Intersection Density	-0.019	0.000	-11.2%	People per Acre	0.008	0.073	+4.3%
Age of Respondent (in years)	-0.020	0.000	-17.0%	Household Income	1.66E-06	0.100	+7.4%	Number of Jobs within a 45min Auto Trip	-1.62E-06	0.044	-7.4%
Household Income	2.17E-06	0.034	+5.2%	Possess a College Degree?	0.179	0.072	**Y**: +10.9%	Age of Respondent (in years)	-0.015	0.007	-8.4%
Is a Student?	-0.369	0.086	**Y**: -17.3%	Is Employed?	-0.196	0.113	**Y**: -8.7%				
Pseudo R-Square: 0.041 **Likelihood Ratio Chi-Square**: 209.68				**Pseudo R-Square**: 0.036 **Likelihood Ratio Chi-Square**: 188.89				**Pseudo R-Square**: 0.141 **Likelihood Ratio Chi-Square**: 684.8			

Mode Choice for Long-Distance *Vacation/Recreation* Travel of 500+ miles	**Mode Choice for Long-Distance *Personal* Travel of 500+ miles**	**Mode Choice for Long-Distance *Business* Travel of 500+ miles**

n = 2,588											
Personal AV											
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	-1.234	0.002		Constant	-1.49	0		Constant	-0.604	0.082	
Jobs per Acre	0.003	0.174	+1.9%	Distance to Transit	-3.23E-06	0.058	-3.7%	Distance to Transit	-2.27E-06	0.148	-2.4%
Household Size	0.069	0.143	+2.2%	Number of Jobs within a 45min Auto Trip	1.44E-06	0.002	+5.8%	Number of Jobs within a 45min Auto Trip	6.06E-07	0.189	+2.2%
Age of Respondent (in years)	0.026	0	+10.0%	Household Size	0.079	0.087	+3.2%	Age of Respondent (in years)	0.029	0	+13.0%
Is Male?	0.288	0.009	**Y**: -3.5%	Age of Respondent (in years)	0.024	0	+11.6%	Is Male?	0.446	0	**Y**: -6.2%
Possess a U.S. Driver's License?	-0.554	0.006	**Y**: -1.3%	Is Male?	0.199	0.066	**Y**: -3.0%	Possess a U.S. Driver's License?	-0.27	0.198	**Y**: -0.7%
Is Caucasian?	-0.389	0.005	**Y**: -3.5%	Possess a U.S. Driver's License?	-0.576	0.005	**Y**: -1.7%	Number of Children in Household	-0.079	0.129	-2.1%
Household Income	-9.10E-06	0	-10.1%	Is Caucasian?	-0.326	0.016	**Y**: -3.6%	Household Income	-3.55E-06	0.001	-4.5%
Possess a College Degree?	-0.402	0	**Y**: -6.1%	Household Income	-6.65E-06	0	-9.2%	Possess a College Degree?	-0.416	0	**Y**: -7.2%
Is Employed?	-0.462	0.001	**Y**: -5.1%	Possess a College Degree?	-0.417	0	**Y**: -8.0%	Is Employed?	-1.11	0	**Y**: -14.2%
Is a Student?	-0.865	0.009	**Y**: -18.9%	Is Employed?	-0.42	0.003	**Y**: -5.9%	Is a Student?	-0.521	0.019	**Y**: -13.0%
Is Retired?	-0.42	0.015	**Y**: -23.5%	Is a Student?	-0.857	0.009	**Y**: -23.4%	Is Retired?	0.778	0	**Y**: +16.9%
				Is Retired?	-0.269	0.116	**Y**: -6.4%				
Shared AV											
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeff.**	**P-value**	**ΔY w.r.t. SD**	**Explanatory Variable**	**Coeffi.**	**P-value**	**ΔY w.r.t. SD**
Constant	-0.353	0.359		Constant	0.129	0.751		Constant	0.111	0.836	
Number of Jobs within a 45min Auto Trip	-1.99E-06	0.001	-8.5%	Number of Jobs within a 45min Auto Trip	-2.00E-06	0.002	-11.7%	Number of Jobs within a 45min Auto Trip	-1.25E-06	0.168	-6.0%
Household Size	0.147	0	+6.3%	Household Size	0.128	0.001	+7.5%	Age of Respondent (in years)	-0.017	0.012	-9.7%
Age of Respondent (in years)	-0.015	0.001	-8.0%	Age of Respondent (in years)	-0.018	0	-12.7%	Household Income	-3.37E-06	0.08	-5.6%
Household Income	-3.32E-06	0.013	-4.9%	Household Income	-1.78E-06	0.162	-3.6%	Is a Student?	-0.654	0.046	**Y**: -21.5%
Possess a College Degree?	-0.173	0.127	**Y**: -3.5%	Possess a College Degree?	-0.194	0.0178	**Y**: -5.4%				
Is a Student?	-0.709	0.005	**Y**: -20.7%	Is a Student?	-0.637	0.008	**Y**: -25.4%				
Pseudo R-Square: 0.057 **Likelihood Ratio Chi-Square**: 273.13				**Pseudo R-Square**: 0.050 **Likelihood Ratio Chi-Square**: 245.96				**Pseudo R-Square**: 0.160 **Likelihood Ratio Chi-Square**: 738.22			

Home Location Choice

The final analysis area of interest is home location choice. Mostly, this section of the research is concerned with where respondents intend to locate their new homes upon the introduction of self-driving vehicles. The sample sizes for these analyses are considerably smaller than those discussed above. This is because these questions were only posed to those respondents considering a move within the next year. Therefore, because of the relatively small sample size, the results should be taken with a grain of salt.

The analysis in this section was regressed using a binomial logit model. The model investigates what may cause a household to move closer to the city center once AVs are available. Both variables of significance are related to destination accessibility. It has been well-established that one's decision of where to locate their home is heavily tied to travel time to important destinations like work (Waddell et al., 2007; Prashker et al., 2008). Therefore, it stands to reason that those living further from their workplace (or school) would express a greater interest in moving closer to the city center. Conversely, those already close to downtown probably do not feel the same draw, as they already enjoy most of the amenities the city provides.

TABLE 6 Model Estimation Results for Home Location Choice with Self-Driving Vehicles

Do You Intend to Move Closer to the City Center Upon the Introduction of AVs? (*n* = 365)			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	-0.027	0.973	
Distance to Work or School	0.023	0.025	+10.4%
Distance to Downtown	-0.025	0.104	-11.9%
Is Not Disabled?	-1.31	0.002	**Y**: -2.8%
Household Size	-0.463	0.048	-19.8%
Number of Workers in Household	0.332	0.091	+10.4%
Age of Respondent (in years)	-0.032	0.041	-16.2%
Is Male?	1.086	0.000	**Y**: +2.1%
Number of Children in Household	0.816	0.001	+24.9%
Possess a College Degree?	0.788	0.015	**Y**: +13.7%
Is Retired?	1.058	0.178	**Y**: +26.9%
Pseudo R-Square: 0.177	**Likelihood Ratio Chi-Square**: 62.46		
Do You Intend to Move Farther from the City Center Upon the Introduction of AVs? (*n* = 365)			
Explanatory Variable	**Coeff.**	**P-value**	**ΔY w.r.t. SD**
Constant	-3.003	0.000	
Jobs per Household	0.001	0.055	+24.7%
Regional Diversity Index	-2.20	0.063	-21.1%
Network Density	0.032	0.069	+15.2%
Household Size	0.390	0.037	+27.9%
Number of Children in Household	-0.506	0.046	-25.8%
Pseudo R-Square: 0.058	**Likelihood Ratio Chi-Square**: 14.50		

CONCLUSIONS

While not all of the “D” variables appear to have a significant influence on one’s indicated self-driving vehicle usage, it is clear that there is a correlation between the built environment and one’s expected use of this new mode of transportation. Through the above analyses some key land use variables arise as predictive of self-driving vehicle adoption and behavior. The two “D” variables which appear most often and show high levels of practical significance are diversity of land uses and destination accessibility. With regards to diversity of land uses, a common thread is that those respondents living in neighborhoods with a poor diversity of land uses express greater interest in AV technology. A limited mix of land uses is associated with higher levels of interest in AVs, higher anticipated use of AV technology, higher likelihood of utilizing DRS, and increased WTP for self-driving capability. It is possible that those living in neighborhoods without a good mix of land uses currently have to travel longer distances and therefore are more interested in the how AVs may improve their travel experience.

Closely related to the diversity of land uses, destination accessibility to non-residential land uses appears to be an important indicator of AV-related behavior as well. If one has limited ability to reach their workplace, the grocery store, or downtown they appear to shower higher levels of interest in AV technology, expect to spend more time in self-driving mode, expect to make greater use of DRS, and are WTP more for AV technology. With regards to job accessibility , no matter the purpose of long-distance travel, it appears when one can reach a greater number of jobs, he or she is more likely to use a personal AV. This may be because those with access to a greater number of jobs can seek out better-paying opportunities and therefore are willing to explore the option of AV travel for lengthy trips.

Home location choice in the presence of AVs is similarly influenced by land use diversity and destination accessibility. Those who are already in areas with a limited mix of uses expect to move farther from the city center, where they will likely encounter similar development patterns. Conversely, those currently living far from their desired destinations anticipate moving closer to the city center. These results are slightly at odds and highlight a need for future research into how land use patterns (like home location) may change upon the introduction of AVs.

The results of the analyses discussed above are useful to a wide range of stakeholders. Planners and engineers can use this information to plan for AVs in the appropriate neighborhoods. For example, this work suggests single-use developments are likely to see AVs before those with multiple uses. Furthermore, manufacturers of AVs may be able to use this information to target potential buyers of their products. This work suggests the focus should be on those who have longer trips from their home to important destinations. Finally, policymakers can use this information to similarly prepare for a future with AVs. Anticipating the spatial introduction of AVs to a region’s transportation network assists local and state governments in preparing for their potential impacts on parking, congestion, and ride-sharing conditions.

AUTHOR CONTRIBUTION

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ACKNOWLEDGEMENTS

The authors would like to thank Scott Schauer-West, Neil Quarles, and Krishna Murthy Gurumurthy for their assistance on this project. Additional thanks are extended to the National Science Foundation's Sustainable Healthy Cities Research Network for its support.

REFERENCES

Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice*, 95, 49-63.

Environmental Protection Agency [EPA] (2014). *Smart Location Database: Version 2.0 User Guide*. https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record* (1780), 87-114.

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. *Journal of the American Planning Association*, 76(3), 265-294.

Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, 40, 1-13.

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, 77, 167-181.

Fagnant, D. J., & Kockelman, K. M. (2016). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation*, 45(1), 143-158.

Gurumurthy, M., & Kockelman, K., (2018). Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. Under review for publication in *Transportation Research Part C: Emerging Technologies*. https://www.caee.utexas.edu/prof/kockelman/public_html/TRB18CAVsurveyMurthy.pdf

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, 78, 37-49.

Kondor, D., Zhang, H., Tachet, R., Santi, P., & Ratti, C. (2017). Estimating savings in parking demand using shared vehicles for home-work commuting. *ArXiv E-prints*. Retrieved from https://arxiv.org/pdf/1710.04983.pdf.

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, 69, 343-355.

Kyriakidis, M., Happee, R., & Winter, J. D. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, 32, 127-140.

Liu, J., Kockelman, K. M., Boesch, P. M., & Ciari, F. (2017). Tracking a system of shared autonomous vehicles across the Austin, Texas network using agent-based simulation. *Transportation, 44*(6), 1261-1278.

Loeb, B., Kockelman, K. M., & Liu, J. (2018). Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. *Transportation Research Part C: Emerging Technologies, 89*, 222-233.

Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). Autonomous vehicles: The next jump in accessibilities? *Research in Transportation Economics*, 62, 80-91.

Navigant Research. (2018, January 29). Navigant Research Leaderboard: Automated Driving Vehicles. Retrieved April 16, 2018, from https://www.navigantresearch.com/research/navigant-research-leaderboard-automated-driving-vehicles

Prashker, J., Shiftan, Y., & Hershkovitch-Sarusi, P. (2008). Residential choice location, gender and the commute trip to work in Tel Aviv. *Journal of Transport Geography*, *16*(5), 332-341.

Quarles, N., & Kockelman, K., (2018). Americans' plans for acquiring and using electric, shared, and self-driving vehicles. Under review for publication in *Transportation Research Record*. https://www.caee.utexas.edu/prof/kockelman/public_html/TRB18surveyFleetEvolution.pdf

Stevens, M. R. (2017). Does compact development make people drive less? *Journal of the American Planning Association*, 83 (1), 7 – 18.

The Milwaukee Sentinel. (1926, December 8). *The Milwaukee Sentinel*, p. 4. Retrieved April 15, 2018, from https://news.google.com/newspapers?id=unBQAAAAIBAJ&sjid=QQ8EAAAAIBAJ&pg=7304,3766749

Waddell, P., Bhat, C., Eluru, N., Wang, L., & Pendyala, R. M. (2007). Modeling Interdependence in Household Residence and Workplace Choices. *Transportation Research Record: Journal of the Transportation Research Board, 2003*(1), 84-92.

Zhang, M. (2004). The Role of Land Use in Travel Mode Choice: Evidence from Boston and Hong Kong. *Journal of the American Planning Association, 70*(3), 344-360.

Zhang, W., & Guhathakurta, S. (2017). Parking Spaces in the Age of Shared Autonomous Vehicles. *Transportation Research Record: Journal of the Transportation Research Board,2651*, 80-91.