AMERICA'S FLEET EVOLUTION IN AN AUTOMATED FUTURE

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ABSTRACT

Cost reductions and technological advancements are priming autonomous, electric, and shared vehicles for rapid growth, which may improve safety and mobility, but also possibly increase vehicle-miles traveled (VMT). This study seeks to improve upon existing fleet evolution work, by simulating adoption of autonomous, electric, and shared vehicles in a single fleet evolution simulation, calibrated with results of a recent survey of Americans. Statistical models are used in the household-level microsimulation to model decisions regarding vehicle transactions, travel behavior, and land use decisions.

The simulation predicts a shift in the powertrain makeup of the United States fleet, with hybrid-electric and plug-in hybrid vehicles each comprising over 40% of the private fleet by 2050, while battery-electric vehicles rise to between 5% and 7%, and gasoline vehicle ownership falls sharply. The rate of decline of the price premium for self-driving vehicle technology has a significant effect on autonomous vehicle (AV) adoption rates, with a 10% annual reduction resulting in adoption rates being roughly 40% higher by year 2050 than with a 5% annual reduction. Allowing the ability to retain a human-driving option in self-driving vehicles results in AV adoption rates being roughly 10% higher by 2050. Shared autonomous vehicle (SAV) use rises to roughly 35% of overall VMT by 2050, about one third of which is via dynamic ride-sharing (DRS). VMT among private vehicles roughly follows adoption rates, though technologies with rising adoption generally experience disproportionately higher VMT, since newer vehicles experience higher VMT than older vehicles.

Keywords: Autonomous Vehicle, Fleet Evolution, Vehicle-Miles Traveled, Vehicle Ownership

INTRODUCTION

Many new travel options are emerging, including electric scooters, electrified buses, and very small aircraft (with vertical take-offs and landings). Among these new modes, self-driving or "autonomous", electric, and shared vehicle technologies are poised for rapid growth. Very-short-term rentals in urban areas launched the relatively new newer concept of shared vehicles and can serve as an alternative to privately-owned vehicles. Ride-sharing en route (with strangers, as in Lyft Shared and Uber Express) has emerged in the last few years, enabled by cell phones, with their GPS. Fully self-driving vehicles, once they become available, will impact these options and others. They can be adopted with or without a human driving option and can be owned privately or shared by multiple users. If self-driving vehicles are shared, they can be dynamically shared among the users by matching the users in real-time. Dynamic ride sharing (DRS) has become possible with smartphone applications and network technologies, while non-DRS represents traditional matching of users for car-pooling. When shared autonomous vehicles (SAVs) are combined with DRS of users, SAVs could increase the demand of motorized-vehicle trips and even undercut the demand of public transit, bikes, and non-motorized modes (Fagnant and Kockelman 2016).

Among various changes expected in the future, this reseach focused on the evolution of powertrain and adoption of autonomous vehicles. In powertrain perspective, the market share of electric vehicles (EVs) might increase because of their advantages over existing gasoline-powered vehicles. EVs can reduce emissions and negative health impacts in many power-generation settings, compared to conventional internal combustion vehicles. Reiter and Kockelman (2017) find a typical EV to generate about half the emissions externalities as that of a gasoline vehicle in Texas cities. Nichols et al. (2015) estimated EVs in Texas to lower emissions of every analyzed pollutant except SO_2 , which increases due to the burning of coal for electricity generation. According to Noori et al. (2015), lower emissions of air pollutants can be achieved with EVs, since EVs have lower environmental damage cost in the US for each air pollutant compared to conventional engines. EVs will lower emissions of all pollutants if generation is shifted away from coal and toward cleaner sources. Many national, state, and local governments have initiatives to accelerate EV adoption, seeking air quality, climate change, and energy-security benefits. As long as generation is sufficient to meet demand, revenues from EV charging may minimize electricity rate increases, while EV owners may be able to save money via overnight charging (Tonachel 2017). Gallagher et al. (2007) even expands this economic effect by arguing that government incentives and changing gasoline price might affect the adoption of EVs and change in powertrain.

Shared and autonomous vehicle technologies may also change the US fleet composition, since SAVs may alter vehicle ownership and demand for various transportation modes. Perrine and Kockelman (2017) indicated that autonomous vehicle (AV) travel may partially replace airline travel, while generating more short-distance travel. It stands to reason that intercity rail and bus modes may also be affected. Fagnant and Kockelman (2014) found that each shared autonomous vehicle may replace 11 personal vehicles but increase vehicle-miles traveled (VMT) by 10%, while decreasing overall emissions. If SAVs entice people to give up personal vehicles, the vehicle fleet may shrink, necessitating less parking space. Increased VMT of SAVs may drive higher vehicle production rates of SAVs, since they will accumulate miles quickly. Thus, the adoption of SAVs would derive different travel characteristics for US vehicle fleets in the future.

LITERATURE REVIEW

Previous work to understand U.S. fleet evolution has included simulation analysis. Bansal et al. (2015) modeled light-duty fleet evolution in Texas regarding fuel efficiency and hybrid-electric vehicle adoption. They used existing Texas Department of Motor Vehicle information to estimate the effects of built environment and demographic factors on choice of hybrid-electric and fuel-efficient vehicles and calibrated their simulation. Paleti et al. (2011) simulated vehicle ownership and travel mileage by vehicle type over time, based on a sample of Californians. They found annual VMT to be higher for larger vehicles. They also analyzed vehicle attributes that may affect choice to purchase electric vehicles.

Kieckhäfer et al. (2014) used a hybrid simulation approach, integrating a system dynamics model with an agent-based discrete choice model, to estimate the evolution of electric vehicle market share. Their simulation modeled the German vehicle market and found that considering individual consumer choices is necessary for an accurate result. Their findings include an expected battery-electric vehicle (BEV) fleet share of about four percent, plug-in hybrid-electric vehicle (PHEV) fleet share of about nine percent, and hybrid-electric vehicle (HEV) fleet share of about twelve percent in the year 2029.

Bansal and Kockelman (2017) surveyed 2,167 Americans to calibrate a 30-year simulation of Americans' adoption of connected and autonomous vehicle technologies, ending in 2045. Their study included all levels of automation and looked at multiple scenarios incorporating different technology price reductions and increases in the population's willingness to pay for the technologies. The study did not include electric vehicles, or shared vehicles.

Musti and Kockelman (2011) microsimulated fleet evolution for 25 years in Austin, Texas, focusing primarily on plug-in hybrid-electric vehicles, calibrated with existing data, as well as a survey of Austinites tailored to understanding fleet evolution. Vehicle choice in the questionnaire was conducted via a series of choices between specific vehicles. This approach may result in biases (Feng et al., 2013), such as brand loyalty, dislike of a particular vehicle model for reasons other than its powertrain or fuel efficiency, or differences in familiarity between models. Their study simulated scenarios including a feebate program to incentivize purchasing HEVs and PHEVs, to help understand what factors may influence future ownership of PHEVs. They suggest 3 percent increase in VMT, while 5 percent decrease in CO_2 is expected in Austin with the feebate program for HEVs and PHEVs. In fleet composition analysis, HEVs and PHEVs are estimated to accout for 25 percent of VMT by year 2034.

Litman (2017) analyzed the impact of AVs in economic context. The benefits and costs of AVs were evaluated in multi-dimensional scale from reduced stress and improved mobility, ownership and operation, safety, and external costs. The results suggest that some benefits from AVs may begin in the 2020s or 2030s, but most impacts that can change the society including reduced congestion, enhanced mobility for low-income people, and energy savings can be observed in the 2040s and 2050s after a meaningful number of AVs have been adopted to the market. Moreover, restricting human-driven vehicles might be necessary due to AV's faster speed, increased traffic volume, and even from reduced investments in public transit.

Paul et al. (2011) used a stated and revealed preference survey to simulate fleet make-up, usage, and resulting greenhouse gas (GHG) emissions in a synthetic population over a 25-year period. The study analyzed how various factors, such as fuel prices, PHEV pricing, feebate policies, and demographic factors. Higher gas prices provided the greatest reduction in GHG emissions and VMT. Higher density development also produced significant reductions in both, while lower PHEV pricing resulted in higher PHEV ownership rates, but increased VMT, and negligible impact on GHG emissions.

While each of these studies provide valuable estimations of fleet evolution, few of them analyzes powertrain, autonomous and shared vehicle technologies in a single fleet evolution simulation. Specifically, the change of powertrain and adoption of AVs is expected in the future US vehicle fleet. The types of powertrain, the adoption of AVs, the proportion of SAVs to privately-owned AVs, dynamic ride-sharing versus non-dynamic ride-sharing, and vehicle ownership are intertwined with each other, so that a holistic approach in a single simulation is necessary. Thus, this study is focusing on the VMT share and vehicle ownership of various powertrains and AVs under different scenarios.

METHODOLOGY

The evolution of the U.S. vehicle fleet is simulated by combining various decision-making models that affect the vehicle ownership, transaction type, AV adoption, usage of SAVs, powertrain, and the moving direction of households. The coefficients of the models were calibrated with a survey data, and these models were run repeatedly from 2017 to 2050 to simulate the evolution of US vehicle fleet.

This study is centered on a household-level microsimulation, which is calibrated with regression models of the responses to the survey conducted in the past. In 2017, stated preference survey data from 1,426 Americans were collected via an online Qualtrics survey, administered by Survey Sampling International. The respondents' travel behavior intentions, opinions, and willingness-to-pay of autonomous vehicles were obtained. The summary statistics of the explanatory variables are shown in Table 1. Based on these statistics, regression models including logit, multinomial logit, and regression results are shown in Tables 4 through 9 in Appendix.

Table 1: Summary Statistics of Explanatory Variables

<table>
<tr><th colspan="3">Variable</th><th>Mean</th><th>St. Dev.</th><th>Median</th><th>Max</th></tr>
<tr><td colspan="3">Household Size</td><td>2.624</td><td>1.311</td><td>2</td><td>10</td></tr>
<tr><td colspan="3">Number of Children</td><td>0.5856</td><td>0.9456</td><td>0</td><td>6</td></tr>
<tr><td colspan="3">Number of Workers</td><td>1.239</td><td>0.9666</td><td>1</td><td>7</td></tr>
<tr><td colspan="3">Number of Vehicles</td><td>1.482</td><td>0.8208</td><td>1</td><td>6</td></tr>
<tr><td colspan="3">Probability of Acquring a Vehicle Within Year</td><td>38.89%</td><td>36.39%</td><td>30%</td><td>100%</td></tr>
<tr><td colspan="3">Distance to Nearest Grocery Store (mi)</td><td>5.128</td><td>5.772</td><td>3.23</td><td>35</td></tr>
<tr><td colspan="3">Household Distance to Nearest Transit Stop (mi)</td><td>7.141</td><td>10.299</td><td>2.07</td><td>35</td></tr>
<tr><td colspan="3">Household Distance to Work or School (mi)</td><td>7.817</td><td>9.563</td><td>3.93</td><td>35</td></tr>
<tr><td colspan="3">Household Distance to City's Downtown (mi)</td><td>10.01</td><td>9.180</td><td>7.31</td><td>35</td></tr>
<tr><td colspan="3">Male ratio</td><td colspan="4">37.24%</td></tr>
<tr><td colspan="3">Driving Alone to Work</td><td colspan="4">50.14%</td></tr>
<tr><td colspan="7">Age Distribution</td></tr>
<tr><td>18 to 24 yr.</td><td>25 to 34 yr.</td><td>35 to 44 yr.</td><td>45 to 54 yr.</td><td colspan="2">55 to 64 yr.</td><td>65 yr. and up</td></tr>
<tr><td>5.96%</td><td>21.46%</td><td>19.64%</td><td>16.41%</td><td colspan="2">17.11%</td><td>19.43%</td></tr>
</table>

The moving direction decision represents the household's intention and direction of moving their location. This was based on two survey questions. Respondents whose households are considering moving are initially asked where their household intends to move in relation to the city center (without mention of AVs or SAVs). Respondents are then asked about how the availability AVs and SAVs would influence where their houshelod would choose to move. Respondents may answer "no effect" or that their household would choose a location the same distance from the city center as they otherwise would have. However, respondents can also answer "closer to the city center than their household otherwise would have" or "farther from the city center than their household otherwise would have".

Using the initial regression values, the simulation produces unrealistic vehicle purchase and release numbers, resulting in roughly a tripling of per-household vehicle ownership by year 2050. To correct for this, the alternative-specific constant (ASC) values are adjusted. ASC is used to represent preferences that are inherent and independent of specific attribute values. This is likely due to errors in estimation by respondents of when future vehicle purchases and releases will occur, and they might have biased preferences in not only in vehicle purchases, but also in other aspects including powertrain and AV options. The maximum number of vehicles owned by a household is limited to the number of adults in a household plus one to avoid households of owning excessive number of vehicles.

Demographics, such as household size and income, do not change during the simulation, and the overall number of households is held constant to eliminate population change as a factor. Thus, all results assume a constant U.S. population over time, rather than adding that additional layer of prediction (of changes in income, household size, etc.). Each respondent's age estimate[1] is used as an explanatory variable in the regression models. While there are multiple people in many households, the respondent's age is an indication of the age of the adults in his/her household. Age increases with every simulation year, until age 80 is reached, at which time the age is changed to 18 years old. Since respondents give age as a range, it is necessary to distribute the households within their age range to a reasonable number of households to roll over from an age of 80 to an age of 18 in every simulation year, instead of all households in each age range rolling over in the same year. To accomplish this, each household's age is distributed according to a random uniform distribution within the age range provided by its respondent.

Model predictions of vehicle ownership, VMT by mode and vehicle type, and average distance from home locations to the city center are reported in the following chapter for the initial year 2017, then every five years, beginning in year 2020. Average annual VMT falls with vehicle age, so the following equation, from NHTSA (Lu, 2006) is used to assign and predict an initial annual VMT to each vehicle, based on its age (A):

$$VMT_{Initial} = 14476.36 - 232.8491 * A - 13.21949 * A^2 + 0.3672131 * A^3 \qquad (1)$$

where A is the age of each simulated vehicle over time. The percentage of VMT from SAV, including DRS VMT and non-DRS VMT can be obtained with the model in Table 6. Then, each household's DRS VMT and non-DRS VMT is subtracted from the household's total VMT, and the remaining "private vehicle VMT" is distributed to each household vehicle proportional to each vehicle's initial (or NHTSA-estimated) VMT.

In the real-world, vehicles can not only be sold or replaced, but also lost because of traffic accidents or reaching its end of life. The owner usually cannot make predictive decisions related to these cases, so these events depend on probability. During the simulation, vehicles can be removed from the simulation because of crashes or reaching its end of life. Based on the current crash rate and scrappage rate of US vehicles (Statista 2016, Statista 2018), the simulation's crash rate is assumed to be 2%, and the oldest vehicle of each household can be totaled with a 2% chance. Therefore, if a household owns only one vehicle, it will be removed from the simulation because of crash or reaching its end of life with the given probability. If a household owns more than one vehicle, the vehicle to be removed from the simulation will be selected randomly. A flowchart outlining the simulation process for each year is shown in Figure 1.

[1] Respondents did not provide their exact age but chose a range or age category. These categories are 18-24 years of age, 25-34, 35-44, 45-54, 55-64, and 65 or more, Rather than choosing the mid-range age for all respondents, ages were assigned uniformly in the range, to allow a smooth and more realistic progression of aging and household shifts over time.

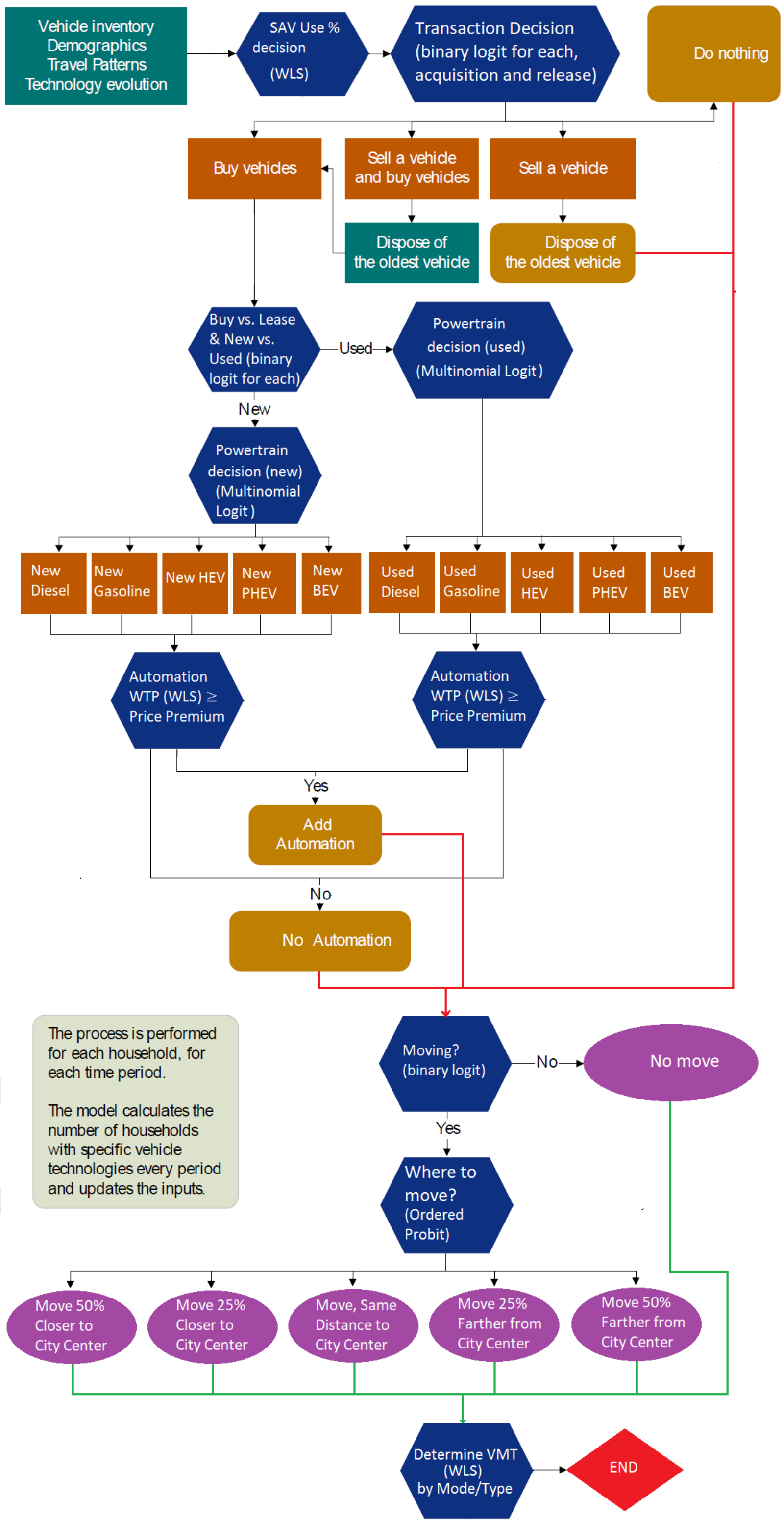

Figure 1: U.S. Fleet Evolution Simulation Flowchart

Six scenarios were simulated, in addition to a business as usual scenario where AVs and SAVs are not available, with two scenarios of willingness to pay (WTP) for full-AV technology each paired with three scenarios of technology price decline. The two WTP scenarios are based upon the survey responses for WTP with and without the option to retain human-driving capability, respectively. The average WTP values given by the survey respondents are $3,252 and $2,783 to add AV technology to their household's next vehicle, with and without retaining an option for human-driving, respectively. WTP values increase over the course of the simulation. An exponential function is likely the most realistic for WTP increase, in the beginning of the AV market, WTP would increase slowly due to the lack of familiarity Americans have with this not-yet-available product. However, extreme cases show that AV adoption may occur earlier than expected in some cities in the US. The two extreme cases in Figure 2, which are 1 standard deviation away from the average WTP, imply that AV adoption may occur earlier in some locations. Upon being suitable and accepted by the majority, most Americans will be able to become more familiar with the technology, so it makes sense that WTP will increase relatively rapidly at that time. This research assumes the WTP for AV technology will increase 5% in each year. For that reason, WTP for all scenarios follows the equation:

$$WTP_{i,j} = WTP_{model,i,j} * (1.05^t) \tag{2}$$

where $WTP_{i,j}$ represents the WTP value returned by the regression model in year t for respondent or household j. This equation is used because it results in average WTP values rising to around $10,000 to $13,000 by year 2050, which may be reasonable as AV technology becomes viewed as universal and necessary for new vehicle purchases. Compare to the initial value, this exponential curve results in a 5% increase in WTP in the first year, which jumps to 63% in the tenth year, and 265% in the twentieth year.

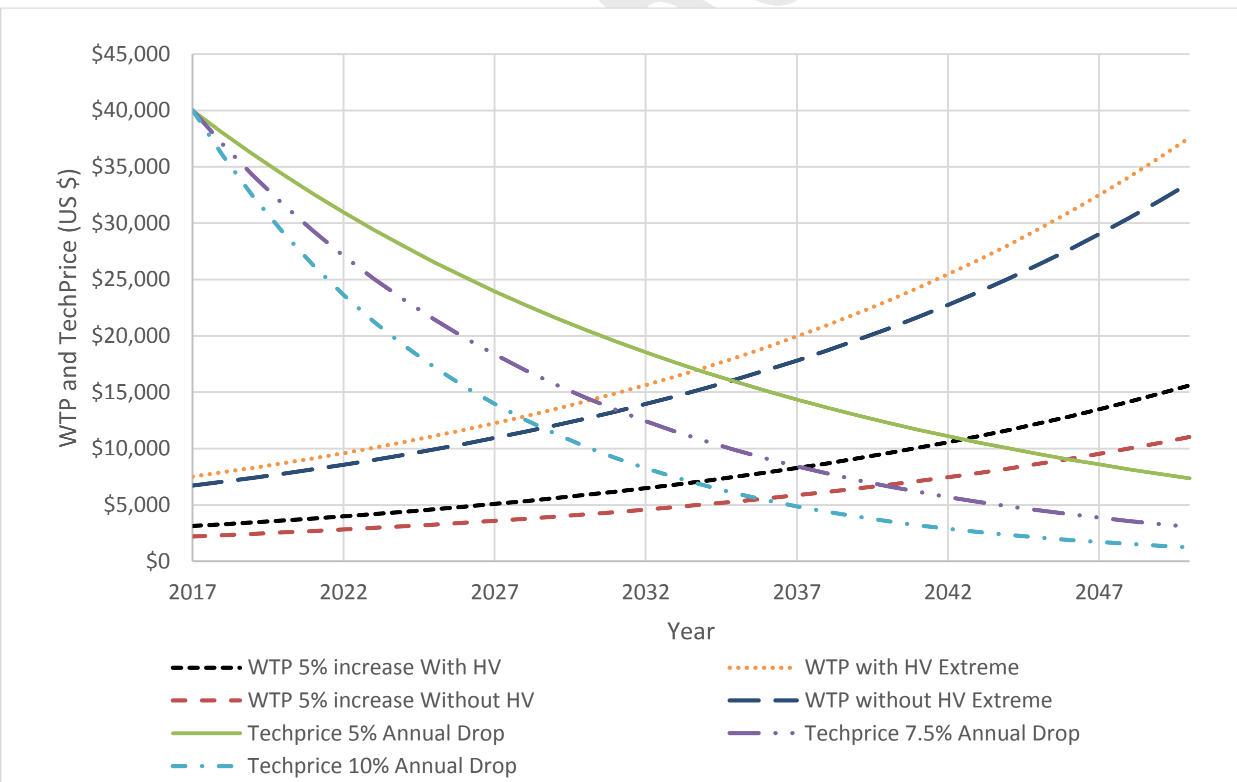

Figure 2: Average Willingness to Pay and Technology Prices for Automation Over Time.

For all scenarios, SAV availability begins in year 2025, but at high prices to represent their limited initial availability (e.g., in New York City, Boston, Pittsburgh, and San Francisco markets first, perhaps) and somewhat higher actual prices. Currently, when including an AV premium for Tesla vehicles, costs range between $8,000 to $11,000 depending on whether it should be added after delivery or not. In order to analyze conservatively, this paper assumed $40,000 for the initial AV technology purchase price premium for all scenarios. Three different scenarios to AV premium are dropping by 5 percent, 7.5 percent, and 10 percent annually. This paper assumes that the techprice of AV will drop by time since the mass production of AV would induce the price of AVs to fall. These price declines result in year 2050 technology premiums of $7,361, $3,053, and $1,236, respectively. Each technology premium scenario is paired with each WTP scenario to generate the six total scenarios in this analysis. While a $1,236 technology price premium may seem low for year 2050, it is possible that features such as connectivity and certain safety features (which would inherently be part of a self-driving vehicle) may be required on new vehicles by then, which could raise the price of human-driven vehicles enough that the additional expense for a self-driving vehicle may drop faster than does the cost to produce the equipment and software that would be necessary to upgrade from currently-available vehicles. Figure 2 shows the technology premiums and WTP over the timespan of the simulation.

SIMULATION RESULTS

Business as Usual Forecasts

A business as usual (BAU) scenario is simulated, in which AVs and SAVs are not available. The simulation was repeated 50 times, and the average values are presented in this paper. Private vehicle powertrain ownership results for this scenario are shown in Table 2 (all vehicles are human-driven). In the powertrain analysis, gasoline-powered vehicles are expected to decrease, while electric and hybrid vehicles will take most of the market share. Specifically, hybrid vehicles (HEV, PHEV) will have more than 80% share of US vehicle fleets in 2050. Hybrid vehicles have advantage over BEVs since they can drive longer distance, and the charging time will be lower or not required compared to BEVs. This suggests a future with more efficient fuel consumption and lower emissions, but one which is still largely dependent on internal combustion engines, especially for longer trips, unless further intervention or breakthroughs occur.

Table 2: U.S. Per-Capita Privately-Owned Light-Duty Fleet Composition with BAU Scenario

Year	Vehicles/HH	Vehicles/HH of Powertrain				
		% Diesel	% Gasoline	% HEV	% PHEV	%BEV
2020	1.96	2.0%	74.2%	12.2%	10.1%	1.5%
2025	1.80	2.1%	45.3%	25.3%	24.1%	3.2%
2030	1.63	2.0%	24.2%	34.8%	34.4%	4.5%
2035	1.54	2.0%	11.5%	40.3%	40.9%	5.2%
2040	1.48	2.1%	6.3%	42.5%	43.4%	5.7%
2045	1.46	2.1%	6.2%	42.6%	43.4%	5.7%
2050	1.46	2.1%	6.2%	42.7%	43.2%	5.8%

Figure 3 shows VMT by powertrain to generally follow vehicle ownership. Some small deviations exist between a given powertrain type's fleet composition and VMT composition. This can be explained by variations in average vehicle age between powertrains (with newer vehicles accumulating more VMT than older ones), differences in total household VMT, and differences in vehicle ownership, which dictates how many vehicles a household's total VMT will be distributed between.

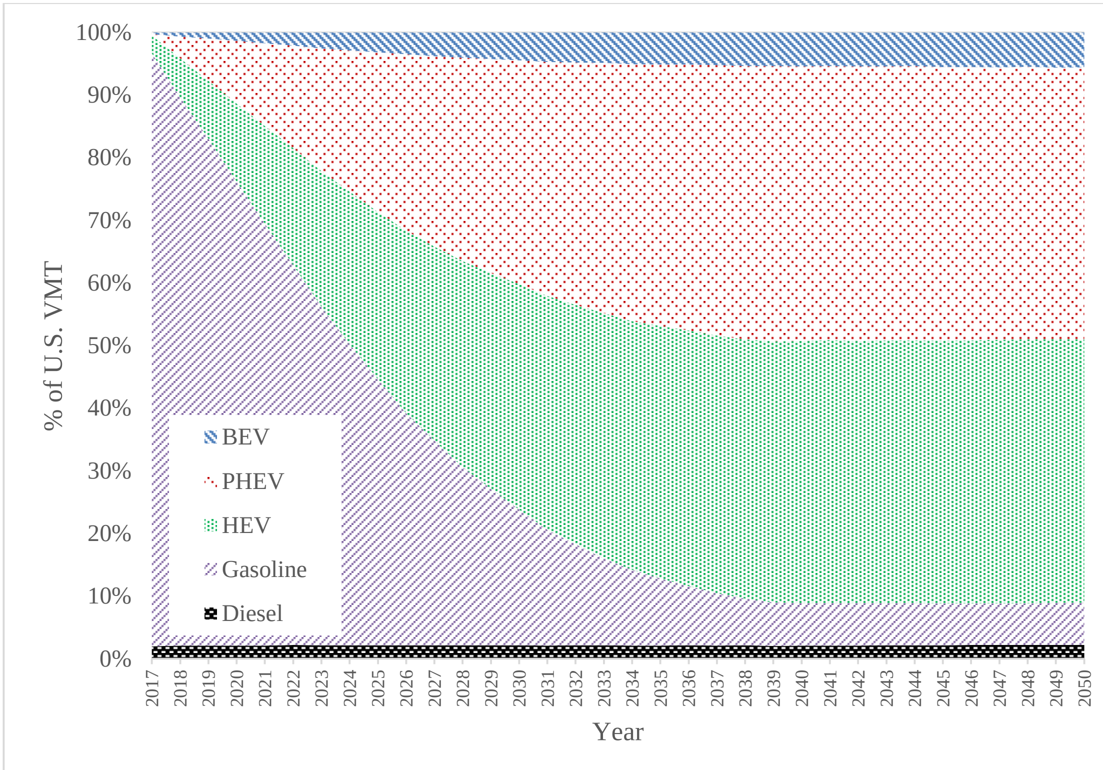

Figure 3: US VMT by Powertrain in a Future without AVs.

5% Annual AV Premium Decline, with HV Capability

Under the scenario of a constant, 5-percent annual decline in an AV's purchase price premium, where human driving (HV) capability is maintained in all fully-autonomous vehicles, Table 3 shows that total vehicle ownership increases during the simulation period. AV ownership doesn't increase until 2040 but begins increasing dramatically after year 2040, to reach almost 40% of private vehicle ownership by year 2050.

Comparing the overall vehicle ownership between this scenario and BAU scenario (Vehicles/HH column in Table 2 and Table 3), AV adoption does not affect the number of vehicles each household will own in the future. It is because AV adoption rate was not included as a variable in the vehicle ownership model of purchasing and releasing a vehicle, because of the uncertainty in predicting future AV adoption. More research should be needed in the future to understand the impact of AV adoption to the vehicle ownership. However, this research captures the change in usage of vehicles, VMT, with the adoption of AV in the US vehicle fleet.

Table 3: US Privately-Owned Fleet Composition with 5% AV Premium Decline & HV Capability

Year	Vehicles/HH	Vehicles/HH of AV or HV	
		% AV	% HV
2020	1.95	0%	100%
2025	1.78	0%	100%

2030	1.62	0%	100%
2035	1.54	0%	100%
2040	1.48	0.97%	99.03%
2045	1.46	13.66%	86.34%
2050	1.45	36.41%	63.59%

In Figure 4, the evolution of VMT by vehicle type is analyzed. AV and HV are privately-owned vehicles, while DRS and non-DRS are shared autonomous vehicles (SAVs). VMT by private AVs rises disproportionally quickly, compared to VMT by HVs, likely owing to the average AV being newer than the average HV as AVs continue to gain market share. In 2050, the VMT from privately-owned vehicles makes up less than 70% of US VMT, while more than 30% is made with SAVs. This result represents that even zero vehicle households can accumulate automobile travel via SAVs, and more flexible travel can be made with the adoption of SAVs. Thus, the adoption of AV technology will provide flexibility to the US transportation network with replacing travels from privately-owned vehicles to SAVs.

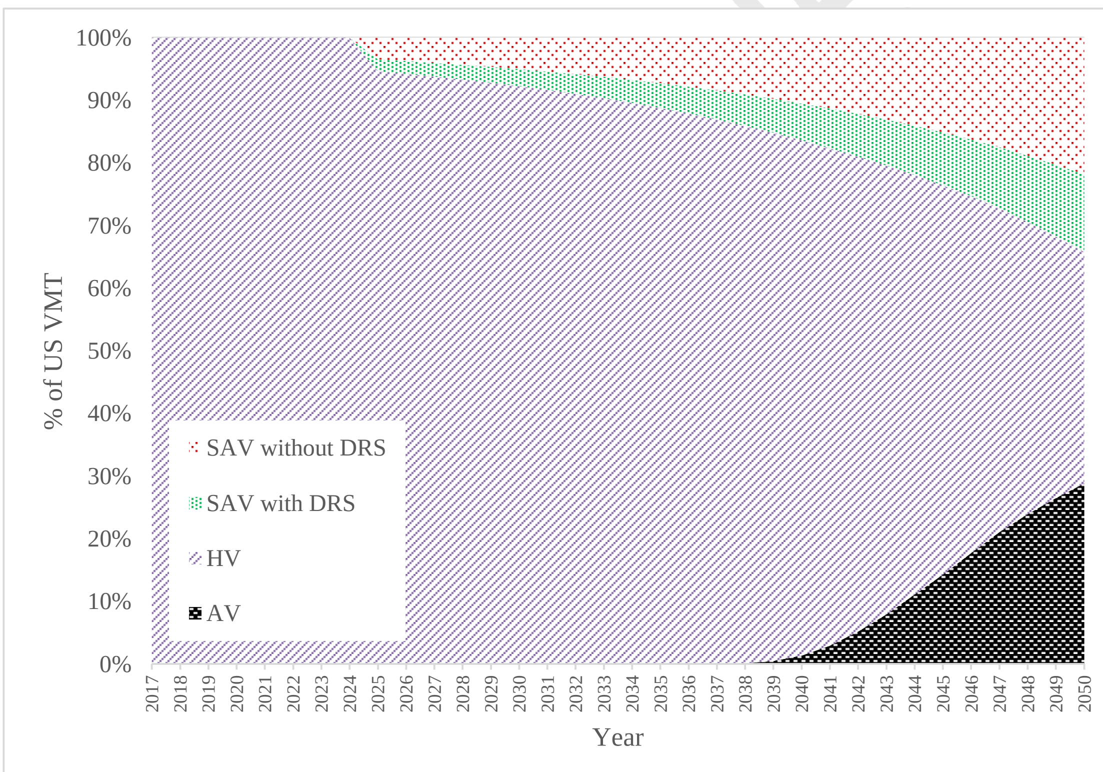

Figure 4: US VMT by Vehicle Type in 5% AV Premium Decline & HV Capability Scenario

Scenario Analysis

In scenario analysis, total 7 scenarios were simulated. The three annual AV premium decline rates, 5%, 7.5%, and 10%, are assumed with and without HV capability. Also, an additional scenario is simulated to explore the effects of mandating full-AV technology on all new vehicles. Since self-driving vehicles may offer safety benefits over human driving, government agencies may seek to enact policies that will shift automobile travel away from humun driving, in favor of autonomous driving. The mandate begins in year

2040, and requires all new vehicles to be fully autonomous, with no option for human driving. A 5% annual AV technology premium decline is used in this scenario.

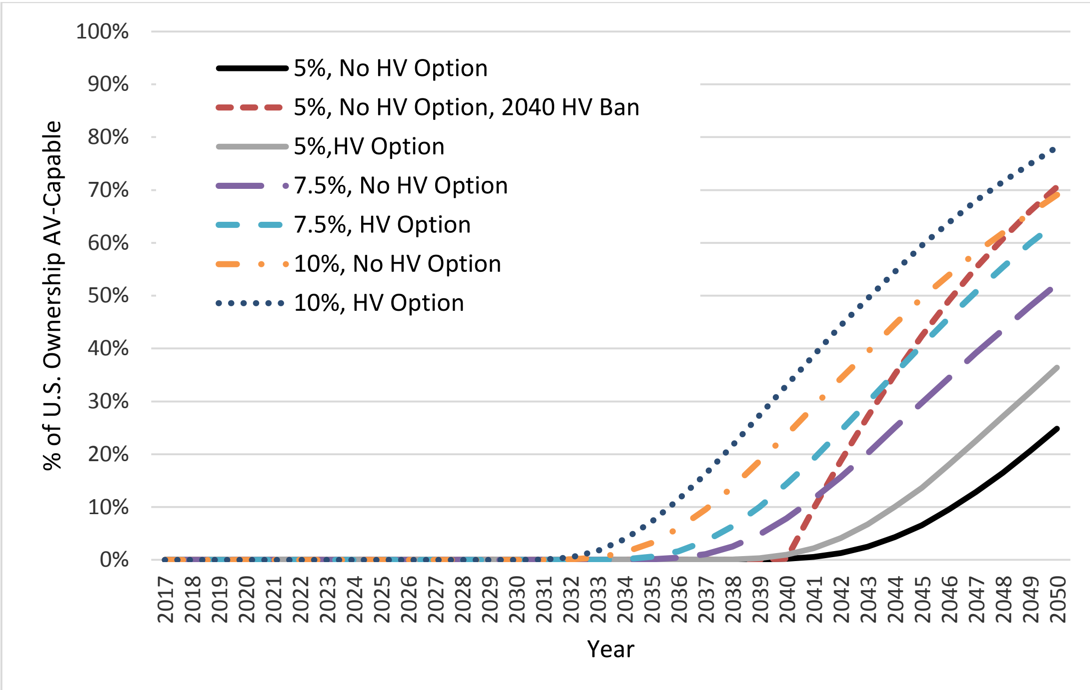

Figure 5: U.S. Vehcle Ownership by percentage of AV-Capable Vehicles for all Scenarios.

Figure 5 shows the composition of AVs in the privately-owned light-duty vehicle fleet for each scenario. There is a roughly 50 percentage point gap between the most optimistic and least optimistic scenarios, and a ban on new human-driven vehicles beginning in year 2040 is shown to alter the least optimistic AV ownership scenario to roughly the ownership numbers of the second most optimistic scenario by year 2050, demonstrating the strong effect of such a mandate.

The scenario analyses suggest that AV adoption rate is highly dependent on the drop rate of techprice over time, which is obvious. Higher drop rate of techprice results in higher market share of AVs. However, the policies and strategies of AV adoption are also key factors affecting AV share. For example, if the drop rate of tech price is same, with HV option has higher rate of AV share than no HV option in 2050. Also, 2040 HV Ban policy derives the second-largest AV adoption rate in 2050. These findings suggest that not only the techprice of AVs, but also the policies and strategies of stakeholders and the government can affect the future of US vehicle fleet.

In all AV scenarios, the VMT share of SAVs increase over time and replaces the VMT of privately-owned vehicles. When specifically analyzed within DRS versus non-DRS, the traditional method of ride-sharing, non-DRS, has higher portion than DRS, so that the tendency of traditional car-pooling may still have higher portion in the future.

Home Location

While the survey respondents indicated that respondents may be influenced by the availability of AVs and SAVs to move closer to the city center than they otherwise would, they also indicated an overall initial preference for moving farther from the city center. The simulation results indicate an overall movement away from the city center, but one that is relatively small. Average increase in home distance from the city center by 2050 ranges from 0.12% to 0.35%. Overall, this is a mild shift away from the city center but may suggest a continued popularity of suburban an exurban living after AVs and SAVs become available to the public.

This suggests a minimal impact of AVs and SAV implementation on home location choice. Furthermore, this implies that urban sprawl and negative impacts from reckless development are not expected or could be minimized when AVs and SAVs are adopted. Perhaps a reduced need for parking space will allow for more infill development in urban areas, providing people ample opportunities to live and work in more compact urban areas.

The results here are dependent on stated preference survey results, asking respondents how transportation technology which they are not familiar with may impact a future home location movement. This unfamiliarity may make it difficult for respondents to have a good sense of how their decisions would be affected. For this reason, further study should be conducted on the effects of AVs and SAVs on home location choice, as well as reactions to the technologies in general, since any study at this stage relies on stated preference data.

CONCLUSIONS

The availability of an option to retain human-driving capabilities in AVs affects their level of adoption and their share of total VMT, due to the higher WTP that exists for AVs if they include that human-driven option. This presents a potential dilemma for policy-makers and AV manufacturers. The potential, safety, congestion, and emissions impacts may make it advantageous to accelerate adoption of AVs as quickly as possible if those effects are determined to provide an overall benefit. However, if a large number of AVs are equipped with the capability for human-driving, a significant amount of VMT in AVs may actually be human-driven, negating a portion of the benefits of shifting the United States fleet toward AVs.

The average respondent indicated an intention to use AV mode for only 35.9% of travel miles in a vehicle that is capable of both human- and self-driving modes, which will result in a lower percentage of VMT in autonomous mode if the human-driven option is retained for AVs, regardless of the price premium scenario. Reasons exist to doubt that self-driving travel would be this low in vehicles capable of both modes. First, this a hypothetical question asked of respondents who have no familiarity with self-driving vehicles, and likely very little understanding of what situations they would choose self- or human-driving modes. Further, the question was asked of all respondents, including those who have little to no interest in AVs. These people are less likely to acquire an AV, especially in early years availability, so those who do acquire AVs are likely more enthusiastic about the self-driving mode and possibly more likely to use it for a larger percentage of their travel in an AV.

Mandating new vehicles to be self-driving might drastically increase AV adoption rates and the percentage of VMT that is self driving, if these vehicles are not allowed to retain an option for human driving. However, if there is significant resistance to a shift to autonomous driving, people owning human-driven vehicles may elect to wait longer to acquire a new vehicle if it is mandated to be self-driving or may elect to acquire a new human-driven vehicle immediately before the mandate takes effect, in a deliberate effort to resist the transition.

Gauging future decisions regarding technologies that people are currently unfamiliar with, and which still carry uncertainty around the conditions of their availability, always carries a high degree of uncertainty. Since this paper provides holistic analysis result of future US vehicle fleets with electrified, autonomous, and shared mobility, the results serve as one estimate of the evolution of the U.S. passenger-vehicle fleet and Americans' ground-based travel patterns, the accuracy of which will be influenced by a number of changing factors, including population age distribution, technological innovations, manufacturer and fleet-operator pricing decisions, and social network effects.

However, this paper is based on 2017 survey results, such that the preference of powertrains, price and tech premium, and relevant infrastructure for each powertrain are assumed to be the same as 2017 as in the future. Thus, it is likely that different powertrains and AV technology could be chosen due to new policies or technological breakthroughs, and the supply of new infrastructures, especially charging stations for EVs, can affect the powertrain share of US vehicle fleets. Nevertheless, this paper provides predicted relationships across various categories, including AV, SAV, powertrains, techprice drop rates, and human driving options.

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APPENDIX

Table 4: Regression Coefficients for Annual Application of Household Moving Choices

Move Decision This Year (Binary Logit, 1 = move)		
Parameter	**Estimate**	**t-statistic**
Intercept	1.0755	2.48 ***
Male	-0.2567	-1.53
Age	-0.0435	-7.23 ***
HHChildren	0.2208	1.75
HHSize	-0.2224	-2.07 ***
HHWorkers	0.2817	2.79 ***
HHVehicles	-0.4504	-4.14 ***
VehPurchYearProb	0.0104	4.56 ***
PTDist	0.0147	2.00 ***
NoDisability	-0.4490	-1.73
DAtoWork	-0.3519	-2.13 ***
(n=1426, Pseudo R^2 = 0.1314)		
Moving Direction Decision (Ordered Probit, y = 1 = *50% closer*, 2 = *25% closer*, 3 = *same distance*, 4 = *25% farther away*, 5 = *50% farther away)*		
Parameter	**Estimate**	**t-statistic**
Ψ_5 (threshold)	-1.2022	-3.53 ***
Ψ_4 (threshold)	0.0243	0.07
Ψ_3 (threshold)	0.8994	2.66 ***
Ψ_2 (threshold)	1.4854	4.36 ***
Male	-0.3690	-2.91 ***
HHChildren	-0.2413	-2.85 ***
HHSize	0.1229	1.72
FullTime or not	-0.7068	-2.61 ***
PartTime or not	-0.7865	-2.70 ***
Student or not	-0.7490	-2.24 ***
Unemployed or not	-0.7614	-2.74 ***
Retired or not	-0.6409	-2.08 ***
HHVehicles	0.1085	1.51
VehPurchYearProb	-0.0023	-1.33
WorkSchoolDist	-0.0109	-1.71
NoDisability	0.2959	1.60
DAtoWork	0.1670	1.32
(n = 365, Pseudo R^2 *= 0.0418,* σ_ε*=1)*		

Table 5: Regression Coefficients for Annual Application of Vehicle Transaction Choices

Decision to Acquire a Vehicle This Year (Binary Logit, 1 = acquire)		
Parameter	**Estimate**	**t-statistic**
Intercept	-0.5018	-1.25

Male	0.4634	3.57 ***
License	-0.6230	-1.71
HHChildren	0.2400	3.71 ***
HHIncome	0.0042	3.24 ***
White or not	-0.2903	-1.81
Student or not	0.4467	1.26
Unemployed or not	0.3919	2.17 ***
PTDist	-0.0161	-2.48 ***
DAtoWork	0.1583	1.23
AgeOldest	-0.0059	-0.64
(n = 1426, Pseudo R^2 = 0.0420)		
Buy (vs. Lease) Decision (Binary Logit, 1 = buy)		
Parameter	**Estimate**	**t-statistic**
Intercept	0.0142	0.03
License	0.5886	1.48
Age	0.0216	3.11 ***
HHSize	0.2628	2.64 ***
HHWorkers	-0.3574	-2.62 ***
FullTime or not	0.4862	1.91
PartTime or not	0.4140	1.37
GroceryDist	0.0725	3.03 ***
(n = 1426, Pseudo R^2= 0.0419)		
Used (vs. New) Vehicle Decision (Binary Logit, 1 = used)		
Parameter	**Estimate**	**t-statistic**
Intercept	1.7654	3.91 ***
Male	-0.4482	-3.28 ***
License	-0.7955	-2.33 ***
Age	-0.0151	-2.70 ***
HHSize	0.0952	1.56
HHWorkers	0.2478	2.85 ***
HHIncome	-0.0094	-5.43 ***
White or not	0.5724	3.26 ***
BachelorsDegree or not	-0.3052	-2.27 ***
FullTime or not	-0.5810	-3.73 ***
Retired or not	-0.2878	-1.31
Married or not	-0.2338	-1.64
VehPurchYearProb	-0.0102	-5.31 ***
WorkSchoolDist	0.0164	2.11 ***
DTDist	-0.0097	-1.32
DAtoWork	-0.3764	-2.51 ***
Dens	0.5027	1.61
(n = 1426, Pseudo R^2 = 0.1304)		

Decision to Release a Vehicle This Year (Binary Logit, 1 = release)		
Parameter	**Estimate**	**t-statistic**
Intercept	-2.1714	-3.90 ***
License	-0.7256	-1.61
HHSize	-0.1589	-2.40 ***
White or not	0.2737	1.41
Retired or not	0.3103	1.47
Married or not	0.2221	1.37
VehPurchYearProb	0.0259	11.99 ***
PTDist	-0.0141	-1.83
NoDisability	0.4181	1.28
DAtoWork	0.3242	1.98
AgeOldest	-0.0065	-0.60
(n = 1426, Pseudo R^2 = 0.1354)		

Table 6: Regression Coefficients for Annual Application of Household SAV Use Choices

Percent of Overall VMT as DRS Decision (Continuous Binary Logit)		
Parameter	**Estimate**	**t-statistic**
Intercept	-1.2387	-20.99 ***
Male	0.0705	4.35 ***
License	-0.1300	-3.62 ***
Age	-0.0125	-18.49 ***
HHChildren	0.0733	8.43 ***
HHWorkers	0.1254	13.02 ***
HHIncome	0.0009	4.70 ***
White or not	-0.0866	-4.61 ***
BachelorsDegree or not	0.1868	11.32 ***
FullTime or not	0.1508	3.25 ***
PartTime or not	0.3469	7.33 ***
Student or not	0.4641	7.91 ***
Unemployed or not	0.1637	3.58 ***
Retired or not	0.3221	6.84 ***
Married or not	-0.0397	-2.22 ***
HHVehicles	-0.1760	-16.76 ***
VehPurchYearProb	0.0085	38.68 ***
GroceryDist	0.0126	8.63 ***
PTDist	-0.0072	-8.10 ***
WorkSchoolDist	0.0077	8.41 ***
DTDist	-0.0022	-2.40 ***
NoDisability	-0.3916	-14.50 ***
DAtoWork	-0.0676	-3.67 ***
Dens	0.0601	2.31 ***

(n = 1426, Pseudo R^2 = 0.0461)		
Percent of Overall VMT as non DRS Decision (Continous Binary Logit)		
Parameter	**Estimate**	**t-statistic**
Intercept	-0.4622	-9.30 ***
Male	-0.0574	-4.25 ***
License	-0.1112	-3.66 ***
Age	-0.0040	-7.05 ***
HHSize	-0.0164	-2.62 ***
HHWorkers	0.1039	11.61 ***
HHIncome	-0.0002	-1.39
White or not	-0.0772	-4.77 ***
BachelorsDegree or not	0.1419	10.36 ***
FullTime or not	-0.5706	-16.40 ***
PartTime or not	-0.3103	-8.77 ***
Student or not	-0.2257	-4.73 ***
Unemployed or not	-0.3086	-9.18 ***
Retired or not	-0.1951	-5.70 ***
Married or not	0.1238	8.31 ***
HHVehicles	-0.0696	-8.07 ***
VehPurchYearProb	0.0072	39.45 ***
GroceryDist	-0.0092	-7.93 ***
WorkSchoolDist	0.0083	10.82 ***
DTDist	0.0010	1.34
NoDisability	-0.3016	-12.73 ***
DAtoWork	0.0496	3.20 ***
Dens	0.1305	5.46 ***
(n = 1426, Pseudo R^2 = 0.0205		

Table 7: Regression Coefficients for Annual Application of Household Willingness to Pay

WTP for AV without HV option (OLS)		
Variable	**Parameter**	**t-statistic**
Intercept	4814.4	8.12 ***
Male	523.80	2.45 ***
Age	-39.199	-5.23 ***
HHChildren	372.18	3.02 ***
White or not	-647.87	-2.40 ***
BachelorsDegree or not	439.35	2.15 ***
Unemployed or not	-821.90	-2.87 ***
Married or not	534.16	2.32 ***
HHVehicles	-443.81	-3.42 ***
VehPurchYearProb	25.581	8.64 ***

GroceryDist	67.124	3.73 ***
DTDist	-16.838	-1.49
NoDisability	-1176.8	-2.99 ***
(n = 1426, R squared = 0.1727)		
WTP for AV with HV option (OLS)		
Variable	**Parameter**	**t-statistic**
Intercept	5142.4	8.94 ***
Age	-53.875	-7.22 ***
HHChildren	210.16	1.73
HHIncome	7.3388	3.20 ***
Student or not	-1127.4	-1.87
Unemployed or not	-1127.3	-4.01 ***
Married or not	544.63	2.35 ***
HHVehicles	-271.91	-2.07 ***
VehPurchYearProb	31.059	10.74 ***
GroceryDist	34.517	1.83
PTDist	-14.953	-1.41
NoDisability	-837.69	-2.17 ***
(n = 1426, R squared = 0.2025)		

Table 8: Regression Coefficients for Annual Application of Household VMT

Overall Annual VMT Decision (OLS)		
Variable	**Parameter**	**t-statistic**
Intercept	452.51	0.65
Male	519.49	1.75
License	2807.1	4.15 ***
HHChildren	475.81	2.94 ***
HHIncome	5.9926	1.82
White or not	866.85	2.36 ***
FullTime or not	1284.5	3.06 ***
PartTime or not	743.22	1.58
Retired or not	822.94	1.85
Married or not	796.22	2.50 ***
HHVehicles	468.50	2.51 ***
VehPurchYearProb	10.278	2.50 ***
GroceryDist	58.939	2.39 ***
WorkSchoolDist	90.846	5.39 ***
DAtoWork	1679.4	4.84 ***
(n = 1426, R squared = 0.2131)		

Table 9: Regression for Annual Application of Powertrain Choices on Vehicle Acquisitions

Powertrain Decision (Multinomial Logit, Gasoline as Baseline)

	Battery-Electric		Plug-in Hybrid		Hybrid-Electric		Diesel	
Variable	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Intercept	-1.3754	-0.90	1.5322	1.31	2.4870	2.20 *	0.9819	0.78
Male	-0.6774	-1.30	-1.4769	-3.65 *	-1.0204	-2.62 *	-1.0120	-2.28 *
Age	0.0111	0.51	0.0128	0.76	0.0215	1.30	0.0192	1.07
HHChildren	-1.1133	-2.61 *	-0.6548	-2.08 *	-0.3132	-1.01	-0.5575	-1.61
HHSize	0.6196	1.83	0.2421	0.86	0.0106	0.04	0.1476	0.49
BachDegree	-0.3376	-0.62	-0.4072	-1.01	-0.3438	-0.86	-0.8427	-1.86
Married	0.0102	0.02	-0.2124	-0.46	-0.6301	-1.36	-0.3815	-0.75
VehPurYrPr	-0.0037	-0.44	-0.0191	-3.04	-0.0168	-2.71 *	-0.0134	-1.96
GroceryDist	0.0031	0.07	-0.0495	-1.52	-0.0854	-2.39 *	-0.0618	-1.66
PTDist	-0.0201	-0.53	0.0288	1.22	0.0095	0.39	0.0338	1.33
WrkSchDist	-0.0210	-0.72	-0.0311	-1.43	-0.0274	-1.27	0.0061	0.27
NoDisabil	0.3269	0.42	0.9088	1.49	0.1166	0.21	0.4334	0.68
DAtoWork	0.3798	0.71	0.4714	1.17	0.5808	1.44	0.0239	0.05
(n = 1426, Pseudo R^2 = 0.0994)								

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