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A Quantitative Investigation into the Impact of Partially Automated Vehicles on Vehicle Miles Travelled in California

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RESEARCH REPORT

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A Quantitative Investigation into the Impact of Partially Automated Vehicles on Vehicle Miles Travelled in California

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16. Abstract

This project investigated changes in travel behavior by owners of partially automated electric vehicles. Partial automation can control vehicle speed and steering using sensors that monitor the external environment. The researchers used review results from survey responses including 940 users of partial automation, of which 628 who have Tesla Autopilot and 312 with systems from other automakers. Autopilot users report using automation more than users of other partial automation systems. Autopilot has the largest impact on travel, notably 36% of Autopilot users reporting more long-distance travel. Respondents who are younger, have a lower household income, use automation in a greater variety of traffic, roads, and weather conditions, and those who have pro-technology attitudes and outdoor lifestyles are more likely to report doing more long-distance travel. The project used propensity score matching to investigate whether automation leads to any increase in respondents' annual vehicle miles travelled. For simplicity, the researchers focused only on the impact of Tesla Autopilot and found that automation results in an average of 4,884 more miles being driven per year.

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Disclaimer

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Executive Summary

Executive Summary

In this study we investigated changes in travel behavior among owners of partially automated electric vehicles. Partial vehicle automation can control vehicle speed and steering with the help of sensors that monitor the environment around the vehicle. Partial automation has the potential to reduce driver fatigue and make driving less stressful; this and the reduced travel costs of electric vehicles could mean drivers choose to travel more.

We use results from survey responses by 940 users of partial automation, including 628 who have Tesla Autopilot and 312 with systems from other automakers. We also present results from 340 users of adaptive cruise control. Autopilot users report using automation more than users of other partial automation systems, and the latter report using automation more than users of adaptive cruise control. Respondents reported using automation most on freeways, in clear weather, and when traffic levels are low. Autopilot users report they are significantly more likely to use their system at night and in stop and go traffic, compared to the users of other systems. Autopilot also has the largest impact on travel; notably 36 percent of Autopilot users report more long-distance travel and 40 percent report driving more in congestion.

The results suggest that some drivers with partially automated systems are more likely to drive their vehicle at congested times of the day and on congested roads, and undertake more long-distance travel, compared to those without automation. Respondents who are younger, have a lower household income, use automation in a greater variety of traffic, road, and weather conditions, and those who have pro-technology attitudes and outdoor lifestyles are more likely to report doing more long-distance travel.

We use propensity score matching to investigate whether automation causes any increase in annual vehicle miles travelled. For simplicity we focus only on the impact of Tesla Autopilot. The results of this model show 4884 more miles per year due to partial automation.

The results of this study suggest that partial automation may increase vehicle miles traveled and may make reaching federal and state emissions targets more difficult. More research is needed on this topic to understand how pervasive the issue could be, especially since partially automated vehicles are available for consumers to purchase and use today.

Contents

Introduction

Electric vehicles have been on the market since 2008-2012 when automakers began offering them for sale. Since then, over two million electric vehicles have been sold in the United States, and over 750,000 in California. At the same time, vehicles are becoming increasingly automated, with many vehicles having Society of Automotive Engineers (SAE) Level 1 or Level 2 automation (see Table 1 for a description of these levels). Some automakers have combined these technologies, so that several models of automated electric vehicles are being sold and used today. These vehicles can be cheaper to run and could reduce driver fatigue because of their automated systems. Previous studies have suggested that *fully* automated electric vehicles could change travel behavior and may increase vehicle miles travelled (VMT) [1, 2]. However, these studies have not focused on this issue for *partially* automated vehicles. Most prior studies on partial automation focus on issues such as how drivers use the technology [3], trust in the technology [4–8], how drivers learn about the technology [9, 10], driver interventions when using automation [11–15], driver training [16], impact on the number of vehicle collisions, legal issues [17], and other topics [18, 19]. In this study we aim to close this gap by investigating how partial automation may change drivers' travel behavior and VMT.

In this study we examine questionnaire survey data from owners of partially automated electric vehicles. We investigate how frequently drivers use the vehicle's automation systems in varying weather and traffic conditions, and on different road types, and any resulting changes to their travel behavior. We then examine factors related to self-reported increases in long distance travel due to vehicle automation. Finally, we use propensity score matching (PSM) to estimate any increase in drivers' annual VMT due to automation using a subset of owners of Tesla partially automated vehicles.

Introduction to Automated Vehicles

Automated vehicles have made considerable progress over the past few years. Many major automotive companies have developed and integrated automated systems into some of their vehicles. Systems are ranked by the SAE into one of five levels of autonomy (Table 1**)**, with Level 0 indicating no automation and Level 5 full automation. Currently, automakers offer systems up to Level 2, also known as Partial Automation. Level 2 systems provide both speed and maneuvering control using radar, cameras, and ultrasonic sensors. Drivers must be ready to take control at any time and give regular input, which is monitored using internal cameras or by detecting whether the driver has their hands on the steering wheel.

Tesla was one of the first automakers to introduce Level 2 automation with its Autopilot system. Systems with similar capabilities include BMW's Driving Assistant, Nissan's ProPilot Assist, Ford's Co-pilot 360, Honda's Sensing, and Toyota's Safety Sense, though some lack the ability to automatically lane change. Limited testing of automated systems by Consumer Reports ranked Tesla Autopilot as having the highest capability and best performance of the four systems they tested, though it was ranked poorly for keeping the driver engaged.

Overall, Cadillac's Super Cruise was ranked higher than Autopilot due to its superior capability in ensuring that the vehicle is operated safely and that the driver maintains their attention (using an internal camera, rather than detecting the driver's hand on the steering wheel) [20].

Table 1. The SAE 5 levels of vehicle automation [21]

SAE Level	SAE Name	Description	Existing Available Examples
0	No Automation	The human driver controls all aspects of driving at all times. The vehicle may have warning systems.	Lane Departure Warning
1	Driver Assistance	The vehicle may be able to control steering or acceleration/deceleration using information from the external environment. The human driver performs all driving tasks.	Adaptive Cruise Control or Lane Keep Assist
2	Partial Automation	The vehicle may be able to control both steering and acceleration/deceleration using information from the external environment. The human driver is considered to be performing all driving tasks.	Adaptive Cruise Control and Lane Keep Assist, Tesla Autopilot, Cadillac Supercruise
3	Conditional Automation	The vehicle can control all driving tasks (steering, acceleration/deceleration) under certain conditions and will not operate unless all conditions are met. The vehicle monitors the environment. A human driver may need to respond to a request to take over the vehicle and acts as the back-up system.	n/a
4	High Automation	The vehicle can control all driving tasks (steering, acceleration/deceleration) under certain conditions and will not operate unless all conditions are met. The vehicle monitors the environment. The vehicle may request a human to intervene though intervention is not necessary.	n/a
5	Full Automation	The vehicle can control all driving tasks (steering, acceleration/deceleration) and monitors the environment. The human could choose the manage the vehicle if they desire, or the vehicle may have no human controls.	n/a

Literature Review

Factors Related to VMT

Several previous studies have focused on understanding the impact of various factors on VMT or travel behavior. These studies have investigated the impact of the built environment [22], fuel price [23], vehicle fuel efficiency [24], access to other transportation modes (public transit, biking, walking) [25], socio-demographics [26], lifestyles and attitudes [27], and the impact of self-selection on VMT and travel behavior [28]. These studies typically found that travel behavior and VMT is related to all of these factors. The density, design, and diversity of urban environments clearly impacts travel behavior [22], though the impact of these local physical characteristics differs based on socio-demographic factors, particularly higher household income which is correlated with increased car ownership [29] and higher VMT [23, 24]. When sociodemographic factors and personal attitudes are controlled for, land use characteristics often are less important [25, 27, 30]. Singh et al. [26] quantify the impact of various factors affecting VMT; they find that 33 percent of VMT is explained by socio-demographics (household structure, household size, income, age), 12 percent by residential density, and 11 percent by residential self-selection. In addition, vehicle fuel economy is also correlated with higher VMT and higher fuel prices with lower VMT [23, 24, 31].

Automated Vehicles and VMT

Researchers are beginning to study the impact of fully automated or driverless vehicles on travel. They have investigated perceptions of the vehicles, whether people would use them, and how they could impact travel and why. Below we review these studies; we focus on them because they are relevant to our study of partially automated vehicles and because there are few studies on partial automation at present. Table 2 summarizes the findings relating to VMT and travel behavior from the literature.

Perrine et al. [33] found that driverless vehicles would lead to increases in long distance travel by around 12 percent. Using National Household Travel Survey (NHTS) data, Schoettle and Sivak [34] modelled the impact of automated shared vehicles on travel behavior, and found that per vehicle VMT would increase by 75 percent, though they assume no increase in total VMT since more vehicles are shard. Wadud et al. [2] used a framework to understand the potential impacts of automated vehicles on energy consumption, travel demand, and carbon emissions. They highlight uncertainty in what impacts the vehicles will have due to the introduction of complementary technologies and other changes in travel behavior. They suggest that the vehicles could have a positive or negative impact on VMT and emissions depending on how they are used. This finding is supported by Childress et al. [35], who found automated vehicles could reduce VMT by 35 percent or increase it by 19.6 percent. Based on traffic simulations, Patella et al. [36] found that fully automated vehicles would increase VMT by eight percent on highways, but only result in a one percent increase in total VMT. One study simulated the use of fully automated vehicles using chauffeur driven cars [37] and found that driverless vehicles could lead to increases in VMT of between four and 341 percent. Automated vehicles clearly have the potential to compact VMT, though most studies find that they could increase VMT. Three recent literature reviews also concluded this [38–40].

The reasons why fully automated vehicles will increase VMT is of particular interest to our study. The reduced cost of travel (due to lower vehicle ownership costs, electrification, lack of diver, etc.) has been found to likely cause an increase in long distance trips, simply because consumers will respond to the reduced cost by travelling more [33, 38]. Increased comfort and a reduced feeling of fatigue has also been found to have the potential to increase VMT [41–43]. Automated vehicles also give consumers the potential to multi-task. Pudāne et al. [43] detected several multi-tasking activities that travelers may engage in, including: working, sleeping, eating, washing, brushing teeth, attending to children, reading, exercising, watching TV, relaxing, and browsing the internet, among other activities. The increased comfort, reduced fatigue, and ability to multitask may lead to consumers put a lower value on time while in an automated vehicle, making them more willing to travel further and more often [33, 44]. These factors may also lead consumers to shift from airplane or train travel in favor of automated vehicles for long distance trips [33, 43]. Increases to VMT would also be seen from driverless vehicles relocating themselves to pick up other travelers [45] and from people sending them out on errands [37]. Studies have also found potential for currently underserved populations (e.g., elderly, less mobile) to travel more [2, 37, 46], though this rise in VMT is offset by societal benefits by increasing these people's mobility.

A small number of studies have examined the effects of partial automation. Hardman et al. [47] found differences in VMT among Tesla owners clustered according to how much they used Autopilot. Frequent Autopilot users had significantly higher annual VMT than did infrequent users and those who did not have Autopilot. This points to a relationship between using Autopilot and VMT, but the study was unable to determine a causal relationship as it did not control for self-selection — i.e., persons with high VMT choosing to buy a Tesla with Autopilot and then using Autopilot frequently. Other studies on partial automation focus on issues such as trust in the technology, perceptions of safety and comfort [4–7], how drivers learn about the technology [9], driver interventions when using automation [14], impact on the number of vehicle collisions, and other issues [18, 19]. We were, however, unable to identify any studies on the impact of partial automation on travel behavior.

Determining Causal Relationships With VMT

One challenge in understanding the causal relationship between any variable and VMT is that the apparent connection may be confounded by self-selection — the possibility that the test subjects may already possess characteristics that affect their responses. For instance, consumers with a desire to travel more may choose to purchase an automated vehicle to assist in them to do so.[1]

Without accounting for self-selection studies may detect spurious relationships, or over (or under) estimate the impact of certain variables on VMT or travel behavior. Since it is not practical to randomly give out automated vehicles to individual households, other means must be employed. Cao et al. [27] and Mokhtarian and Cao [32] suggest ways in which self-selection biases can be addressed using various methods relevant to our study.

The methods outlined by Cao et al. are: direct questioning, statistical control, instrumental variable models, sample selection models, propensity score models, simultaneous models, and longitudinal designs. The direct questioning, statistical control, and propensity score methods are of interest to our study as we have or can obtain the data needed for these methods. In the *direct questions* approach survey takers or interviewees are directly asked about the relationship between their travel behavior and any self-selection biases that could exist. Cao et al. note that this method, though simple, can provide more valuable insights than more complex methods, though they caution it can be affected by sample bias, memory bias, social desirability bias, or any other biases common in consumer studies. This study specifically asked participants to estimate how much their driving changed from using an automated vehicle.

With *statistical control* attitudinal and lifestyle variables are directly incorporated into a model as controls. Care needs to be taken to ensure all relevant attitudes are recorded in the survey and included in the model. Most household travel surveys don't contain any lifestyle variables, meaning additional surveys are needed. This study included numerous attitudinal and lifestyle questions to overcome this problem.

Finally, *propensity score matching (PSM)*, or stratification, can be used to mimic randomized experiments, whereby the matching method provides some assurance that the likelihood of being part of either the treatment or control groups is governed by random chance. In observational studies such as this one, it is not possible to be sure that other factors may not have influenced the initial choice to obtain an automated vehicle or not. With PSM, surveyed households with automated vehicles are matched to those without based on all observed household characteristics to create two sets of participants to compare that are as alike as possible. In this study, participants with similar age, income, sociodemographic and other characteristics, for instance, would likely share similar desires for travelling. As a result, the effect on travel behavior of using automation or

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[1] As another example, the impact of residential location self-selection on travel behavior has been given some attention in the literature. Residential self-selection has the potential to impact travel behavior studies as consumers may choose to reside in areas that are conducive for their preferred transportation modes, e.g., those who like biking may choose to reside in bike friendly areas. In this example the impact of biking infrastructure on the decision to use a bike could be overestimated.

not can then be measured, for example, as the difference between the two groups' mean annual VMT. One should note, the PSM method may not give reliable estimates if there are unobserved factors that are a source of self-selection bias. Hence, it is essential to control for all the relevant population characteristics in the matching process.

In summary, the problems of self-selection bias can be addressed with direct questioning, statistical controls and PSM. We employ each of these three methods in this study. The results are described below.

Table 2. Summary of literature on potential VMT increases from automated vehicles and the reason for these increases

	Potential changes to travel behavior	Reference
Where VMT increases could be seen	More long-distance trips	[33, 37, 41]
	More local trips	[37]
	Mode shift from airlines	[33]
	Residential location change	[40, 44]
	Workplace location change	[44]
	Empty vehicle miles - errands	[37]
	Empty vehicle miles - relocation	[45]
Why VMT could increase	Reduced travel costs	[33, 38]
	Reduced stress and fatigue and increased comfort	[41–43]
	Demand from new users (e.g., older people)	[2, 37, 46],
	Easier to go out drinking	[37]
	Ability to multitask	[37, 43]
	More willing to drive at night	[37]
	Lower value of time while travelling	[33]
	Improved traffic flow and reduced travel times	[35]
	Reduced parking costs	[35]
	Miles shifting between vehicles	[45]

Note: table adapted from [48]

Analysis

In this study, we used a cohort survey of Plug-in Electric Vehicles (PEV) owners in California administered by the authors in November 2019. Respondents had been previously surveyed by the UC Davis Plug-in and Hybrid & Electric Vehicle (PH&EV) Research Center between 2015 and 2018 as part of four surveys in the eVMT project when they originally bought their PEV. Respondents for the four phases of the eVMT survey were sampled from the pool of PEV buyers who had applied for the state rebate from the California Vehicle Rebate Program (CVRP). More than 25,000 PEV owners were surveyed between 2015 and 2018. A total of 15,000 of these respondents gave consent to be re-contacted and were invited for the repeat survey in 2019. In all, 4,925 PEV owners responded to the repeat survey. The sample is a convenience sample.

Most survey respondents have several vehicles in their household. In this study, we consider the vehicle most frequently used by the survey taker. We asked survey respondents how they used this vehicle, whether it has automation, and how often they use the automated features of the vehicle.

The surveys contained the following sections:

- Household information including number of vehicles in the household, number of people in the household, age and gender of household members, number of licensed drivers, household income, home type (e.g., single family home or multi-unit dwelling), and home ownership.
- Information on household vehicles including make, model, year of purchase, and odometer readings.
- Electric vehicle charging behavior, including location of charging (e.g., home, work, or public charging), and whether respondents have access to free charging.
- Travel behavior questions, including home and work locations, which are used to determine commute distance, and information on long-distance trips.
- The importance of incentives in the decision to purchase a PEV, including the U.S. Federal tax credit, California Clean Vehicle Rebate, High Occupancy Vehicle (HOV) lane access, and other local incentives (e.g., from utilities).
- Twenty-two lifestyle statements which are used to generate eight attitudinal/lifestyle factors (see section below).
- How often the participants use automation on a continuous slider bar scale from never (0 percent of trips) to every trip (100 percent of trips); how much they use automation on their commute (0-100 percent of the commute distance); and how much they used it on their longest trip in the last 12 months (0-100 percent of the trip distance).
- How likely respondents are to use automation on different roads (interstate or freeway, urban roads, rural roads, on/off ramps, parking lots), and under different conditions (clear weather, night, rain, fog), and traffic levels (fast moving traffic, slow moving traffic, stop and go traffic, empty road). The participants could answer this on a 5-point Likert scale from Very Likely to Very Unlikely.

- If the respondents believed their travel patterns had changed as a result of automation, with separate questions for "Local Travel (commuting, errands, grocery shopping, etc.)" and "Long Distance Travel (weekend travel, vacation trips, etc.)." The participants could answer this on a 5-point Likert scale from Far Less Travel, through No Change, to Far More Travel.
- Questions on how their travel would change if for some reason they could not use automation any more. Respondents were asked "If for some reason you were no longer able to use [automationtype] how likely would you be to do the following?" for: Change Time of Commute to Avoid Congestion, Use Different Travel Mode, Change Route to Avoid Congestion, Reduce Number of Local Trips, Reduce Number of Long-Distance Trips, and Share a Ride.

Statistical Analysis

We use descriptive statistics to investigate the use of different automated systems (adaptive cruise control only, adaptive cruise control and autosteer, and autopilot). We use Tukey test for pairwise comparisons of means and Chi square tests for categorical variables. These tests investigate differences in the use of automated systems in different weather types, road conditions, traffic conditions, and use on long distance trips, all trips, and respondents' commutes. We use a binary logistic regression model to investigate factors correlated with the decision to undertake more long-distance travel due to vehicle automation. We estimate a model for users of all levels 2 automated systems (adaptive cruise control and autosteer, and Tesla Autopilot), and a separate model for Tesla Autopilot only. Finally, to estimate the VMT increase caused by level 2 automation we use propensity score matching. We use a model of only Tesla Autopilot users to simplify the complicated issue of determining causality. For full detail on methods see Appendix- Statistical Analysis.

Results

Sample Description

Figure 1 shows a count of the automated systems survey respondents have in their most frequently used vehicle. The most common is Tesla Autopilot; this is largely a result of the PEV market being dominated by Tesla. Other common systems in the sample are BMW's Driving Assistant, Ford's Co-pilot 360, Honda's Sensing, Nissan's ProPilot Assist, and Toyota's Safety Sense. While most of these systems have some form of speed control (Adaptive Cruise Control, Traffic Aware Cruise Control, or Dynamic Radar Cruise Control) and some sort of steering assistance (Autosteer, Lane Centering, or Lane Keeping Assist) not all owners of vehicles with these systems reported using both steering assistance and speed control. This may be because respondents do not use both capabilities or they are not aware of them. Of the 652 survey takers that have a non-Autopilot automation system 340 reported only using some type of adaptive cruise control while 312 reported using adaptive cruise control and autosteer. We therefore breakdown the analysis by those who use Autopilot, those who use adaptive cruise control and autosteer (from any non-Tesla brand), and those who use only adaptive cruise control (from any non-Tesla brand).

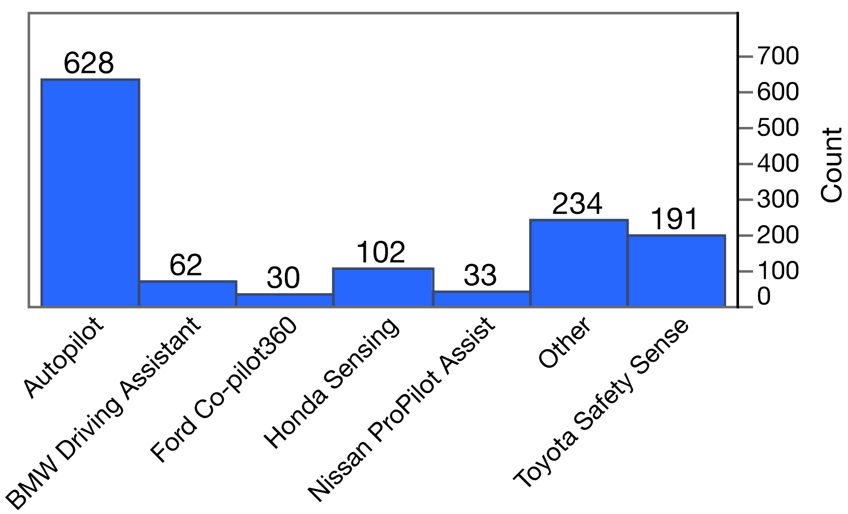

Figure 1. Automated systems of vehicles owned by survey respondents who have vehicle automation

Frequency of Automation Use

Figure 2 shows that those with Autopilot and those with adaptive cruise control and autosteer report a higher frequency of automation use during any trip compared to those with only adaptive cruise control. Drivers using Autopilot report higher frequency of use of automation than the users of other automation systems. The Tukey test in Table 3 shows that there is a statistically significant difference in frequency of automation use by those with the Autopilot feature and those with autosteer and adaptive cruise control as well as those with only adaptive cruise control. The difference is also significant between those with adaptive cruise control and autosteer and those with just adaptive cruise control.[2]

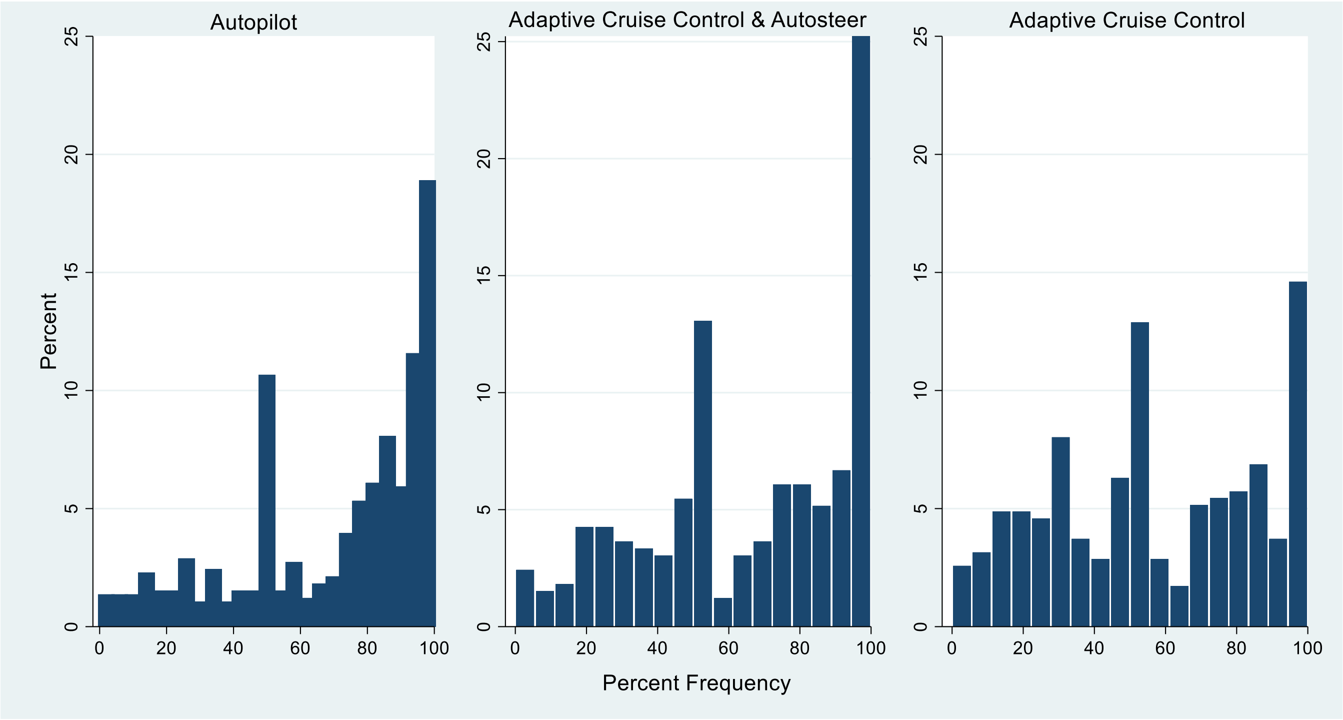

Figure 2. Answers to "How frequently do you use [automationtype]?" on a scale from Never (0%) to Every Trip (100%).

Respondents were shown a map of their reported commute and asked on what percentage of that journey they used automation. Figure 3 shows that on average users of Autopilot use automation on higher percentage of their commute than users of adaptive cruise control and autosteer and adaptive cruise control only. Adaptive cruise control was reportedly used the least on drivers' commutes with a high proportion indicating they do not use the feature at all. The Tukey test results in Table 3 show that there is a significant difference between the use of Autopilot and adaptive cruise control only, and between adaptive cruise control and autosteer and adaptive cruise control only. There is no significant difference between adaptive cruise control and autosteer use and Autopilot use on commute.

[2] Tukey tests were used on the questions on frequency of automation use and the questions on the impacts of automation on travel decisions to find if there were statistically significant differences between reported use of Autopilot, adaptive cruise control and autosteer and adaptive cruise control only. A 95 percent significance level was used for all Tukey tests.

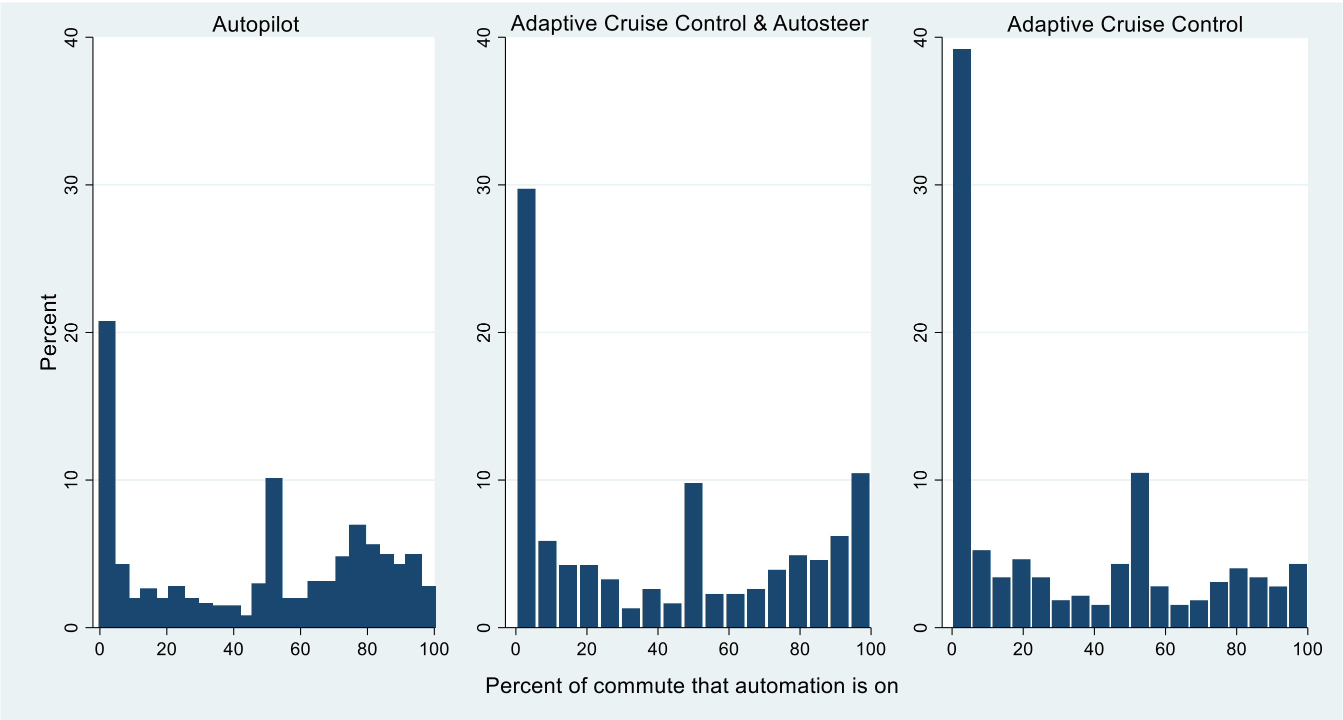

Figure 3. Answers to "You previously indicated that this was your commute [map shown], which is a distance of [n] miles: How much of this trip do you estimate is done using [automationtype]?"

Respondents were shown a map of their reported longest trip in the last 12 months and asked on what percentage of that journey they used automation. Figure 4 shows that respondents in all three groups report using automation more on their long-distance trips compared to on their commute on average. This is perhaps due to long distance trips being primarily done on highways, interstates, and freeways. The Tukey test in Table 3 shows that the differences in use are not significant between users of the three different automation types.

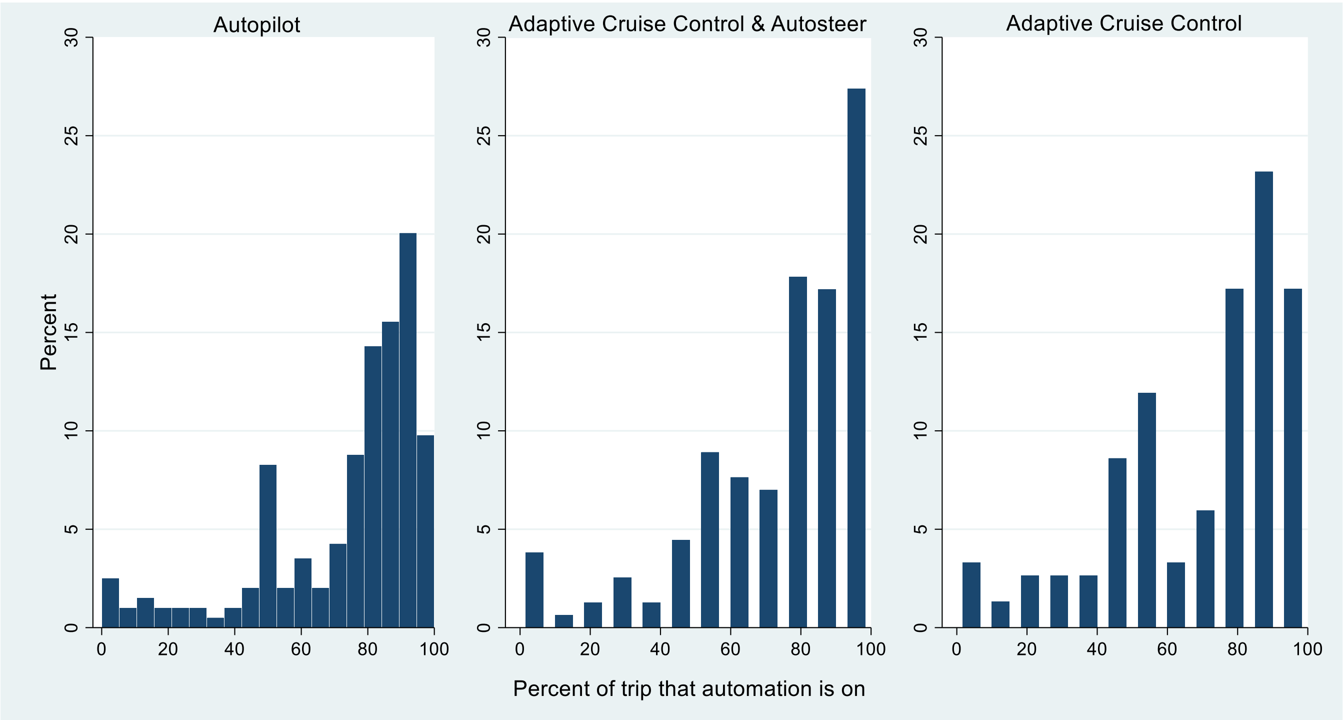

Figure 4. Responses to "You previously indicated that this was your longest trip in the last year in your [automationcar]. How much of this trip do you estimate is done using [automationtype]?"

Table 3. Tukey test for pairwise comparison of means for frequency of automation use, percent of automation use on commute, and percent of automation use on longest trip. Significant values are red.

	Automation Type	Mean	Auto Levels Comparison	Contrast	Std. Err.	P>|t|
Frequency of Automation Use	Autopilot	70%	Adaptive Cruise Control & Autosteer vs Autopilot	-0.284	0.117	0.040
	Adaptive Cruise Control & Autosteer	65%	Adaptive Cruise Control vs Autopilot	-0.817	0.114	0.000
	Adaptive Cruise Control	57%	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-0.533	0.133	0.000
Percent of Commute Using Automation	Autopilot	47%	Adaptive Cruise Control & Autosteer vs Autopilot	-5.518	2.405	0.057
	Adaptive Cruise Control & Autosteer	41%	Adaptive Cruise Control vs Autopilot	-15.162	2.361	0.000
	Adaptive Cruise Control	32%	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-9.643	2.731	0.001
Percent of Longest Trip Using Automation	Autopilot	74%	Adaptive Cruise Control & Autosteer vs Autopilot	-0.467	2.284	0.977
	Adaptive Cruise Control & Autosteer	74%	Adaptive Cruise Control vs	-4.349	2.316	0.146
	Adaptive Cruise Control	70%	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-3.882	2.763	0.339

Automation Use by Road Types

Figure 5 shows a comparison of drivers' reported use of adaptive cruise control (top row), adaptive cruise control and autosteer (middle row), and Autopilot (bottom row) on different road types, Table 4 shows chi-square test comparisons of these distributions.[3] Users of all three automation types are most likely to use the system on freeways. Users of Autopilot report being more likely to use it on freeways then users of the other systems. Users of adaptive cruise control report being less likely to use the system on urban or rural roads then users of adaptive cruise control and autosteer and users of Autopilot.

[3] Chi Squared tests were used on the following categorical questions: automation use by road type, weather conditions, and traffic conditions, questions to find if there were statistically significant differences between reported use of Autopilot, adaptive cruise control and autosteer and adaptive cruise control. A 5 percent significance level was used as a criterion for rejecting the null hypothesis.

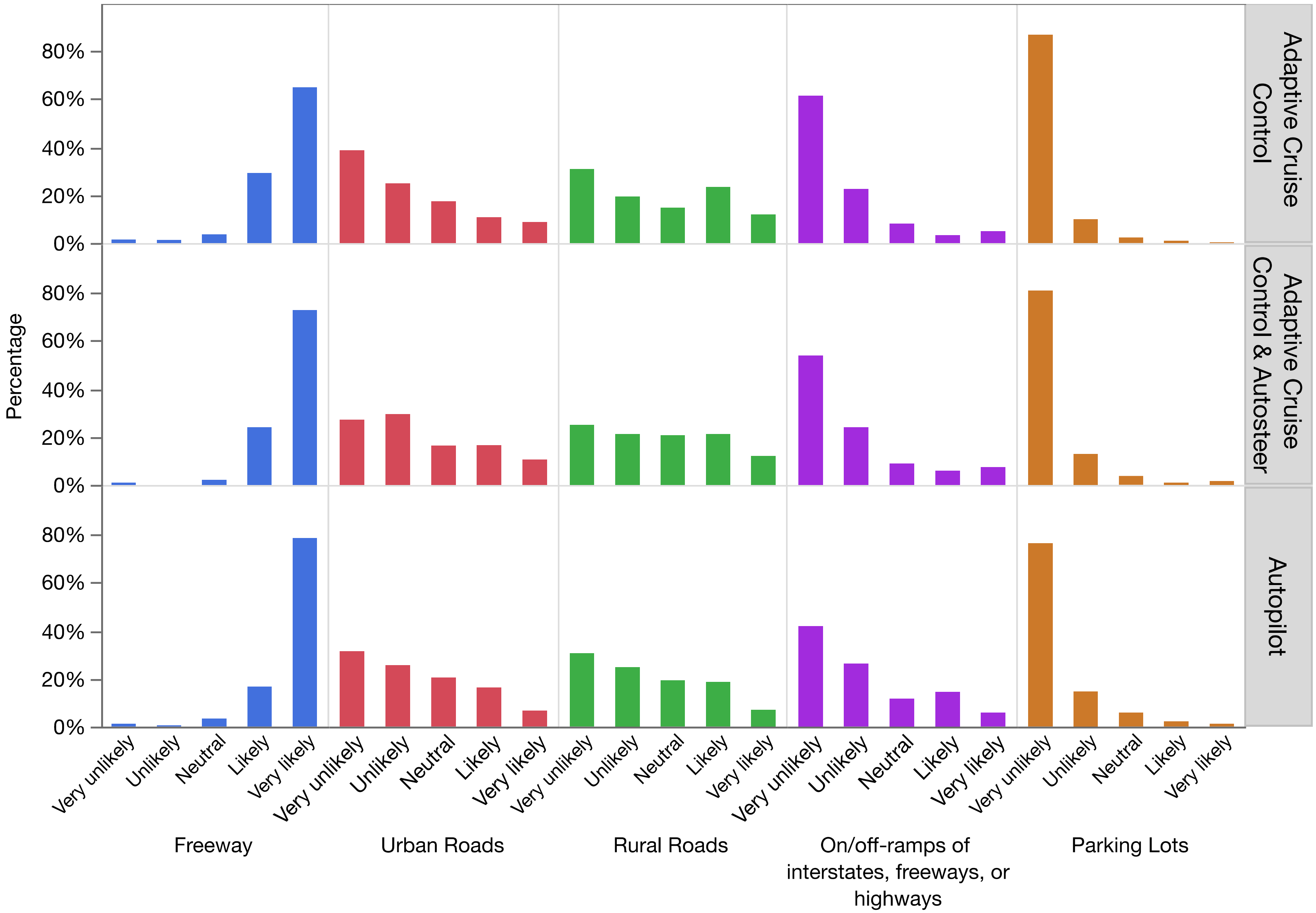

Figure 5. Answers to "On which types of roads are you likely to use [insert automation type]?"

Table 4. Chi square test comparison for responses to "On which types of roads are you likely to use [automationtype] for those with Autopilot, adaptive cruise control, and adaptive cruise control and autosteer for the 5 road types listed. Significant values are red.

Type of Road	Chi Square Value	Pr
Freeways	33.8516	<0.001
Urban Roads	23.9435	0.002
Rural Roads	19.7365	0.011
On/Off Ramps of interstates, freeways, or highways	58.4878	<0.001
Parking Lots	23.6791	0.003

Automation Use by Weather Conditions

Figure 6 shows a comparison of drivers' reported use of adaptive cruise control (top row), adaptive cruise control and autosteer (middle row), and Autopilot (bottom row) in different weather conditions, Table 5 shows chi-square test comparisons of these distributions. Respondents are very likely to use the automated systems in clear weather and likely at nighttime. Drivers are less likely to use any automation system during rain and fog and are very unlikely to use automation systems during snow. These distributions are significantly different with Autopilot drivers reporting they are more likely than other drivers to use their automation system during any weather conditions, including in rain, fog, and at night.

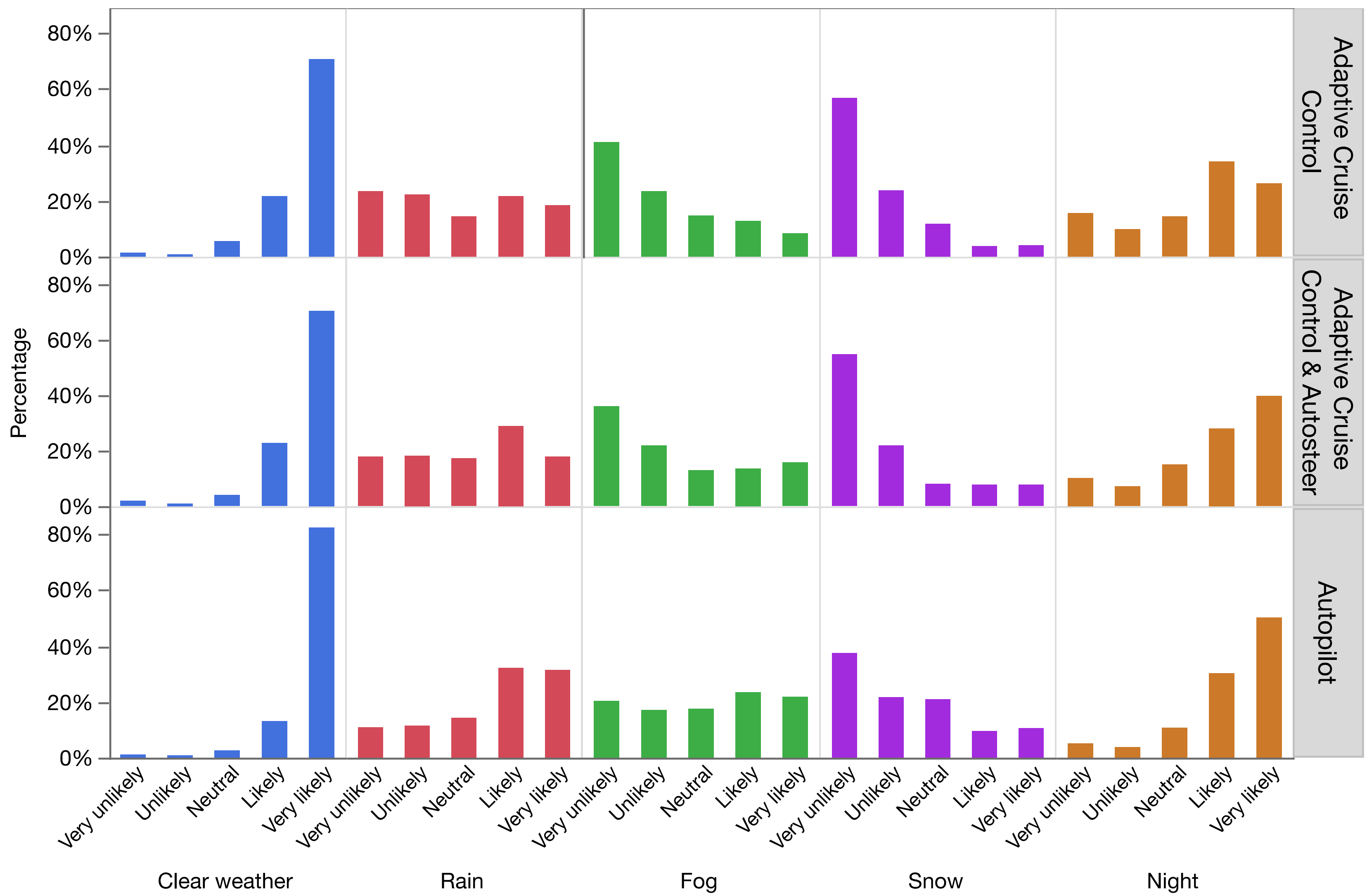

Figure 6. Answers to "In which conditions are you likely to use [insert automation type]?"

Table 5. Chi square test comparison for responses to "In which conductions are you likely to use [automationtype] for various weather conditions. Significant values are red.

Type of Weather Conditions	Chi Squared Value	Pr
Clear Weather	28.6712	<0.001
Rain	76.8872	<0.001
Fog	92.8904	<0.001
Snow	75.4366	<0.001
Night	83.2057	<0.001

Automation Use by Traffic Conditions

Figure 7 shows a comparison of drivers' reported use of adaptive cruise control (top row), adaptive cruise control and autosteer (middle row), and Autopilot (bottom row) in different traffic conditions, Table 6 shows chi-square test comparisons of these distributions. Users of all three automation types are very likely to use their automation systems on empty roads and in fast moving traffic. Autopilot drivers report being significantly more likely to use their automation system in all traffic conditions, though the differences for use during both slow-moving traffic and stop and go traffic show greater divergence of use in these conditions

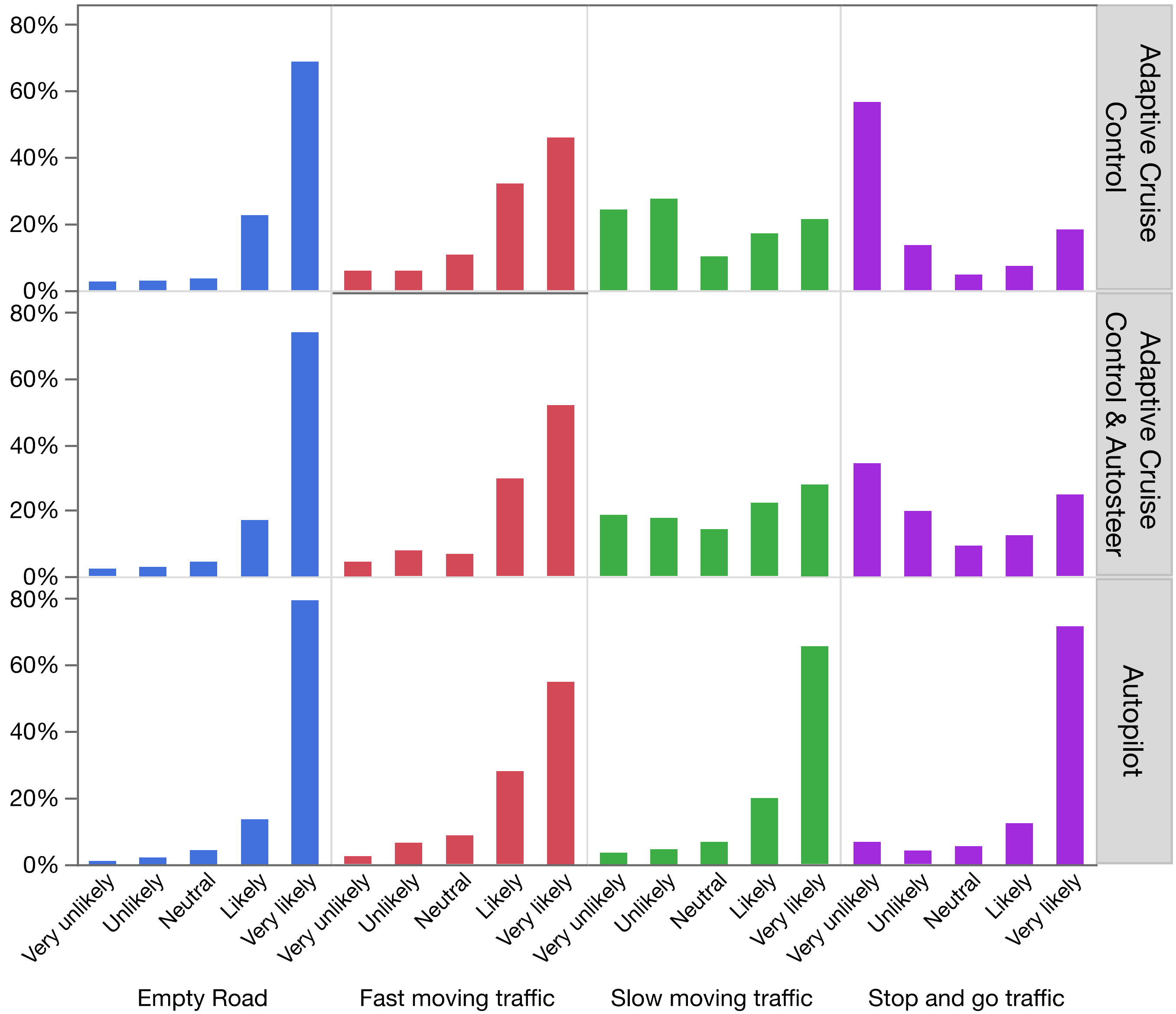

Figure 7. Answers to "In which traffic conditions are you likely to use [insert automation type]?"

Table 6. Chi square test comparison for responses to “In which traffic conditions are you likely to use [automationtype]?” for various traffic conditions. Significant values are red.

Traffic Conditions	Chi Squared Value	Pr
Empty Roads	20.2447	0.009
Fast Moving Traffic	19.426	0.013
Slow Moving Traffic	333.1516	0.000
Stop and Go Traffic	483.7195	0.000

Impacts of Automation on Travel Decisions

To understand the potential impacts of automation on drivers travel decisions respondents were asked “If for some reason you were no longer able to use [automationtype] how likely would you be to do the following?” for six different scenarios. The results of these are shown in Figure 8 to Figure 13. Respondents were asked in this way in an attempt to isolate the impact of automation from other features of the vehicle they own, notably because they are electric vehicles, as respondents may have made changes to their travel since owning an electric automated vehicle not only due to automation. By asking respondents how they would change their travel if they could not use automation other aspects of their vehicle remain the same. If respondents report they are likely to make a change to their travel due to not being able to use automation we interpret this as being something which automation is currently impacting. For example, if respondents report that they would change the routes they take to avoid congestion if they could not use automation, we interpret this to mean drivers do not seek to avoid congestion in their vehicle because of automation. For users of all systems and for all potential changes to travel more respondents are unlikely to make this change than likely. This does not mean the changes to travel are not occurring though, for some changes 40 percent of respondents report being likely to do this (e.g., Autopilot users’ likelihood to change the routes that they take to avoid congestion if they could not use Autopilot).

Figure 8 shows on average drivers report they would be unlikely to change the time they drive to avoid congestion if they were no longer able to use automation. However, 38 percent of Autopilot users, 26 percent of adaptive cruise control and autosteer, and 22 percent of adaptive cruise control users report being likely to do this. This suggests the automated systems do have an impact on drivers being more willing to drive in congestion due to the presence of automation, and that without automation some respondents would attempt to avoid driving at congested times of the day.

The statistical comparisons in Table 7 show that more users of Autopilot indicated they would be likely to change their time of commute than the other two groups. The differences in these distributions are significant between responses by users of Autopilot compared to adaptive cruise control and autosteer and adaptive cruise control only. The distribution between adaptive cruise control and autosteer and adaptive cruise control only users are not significantly different.

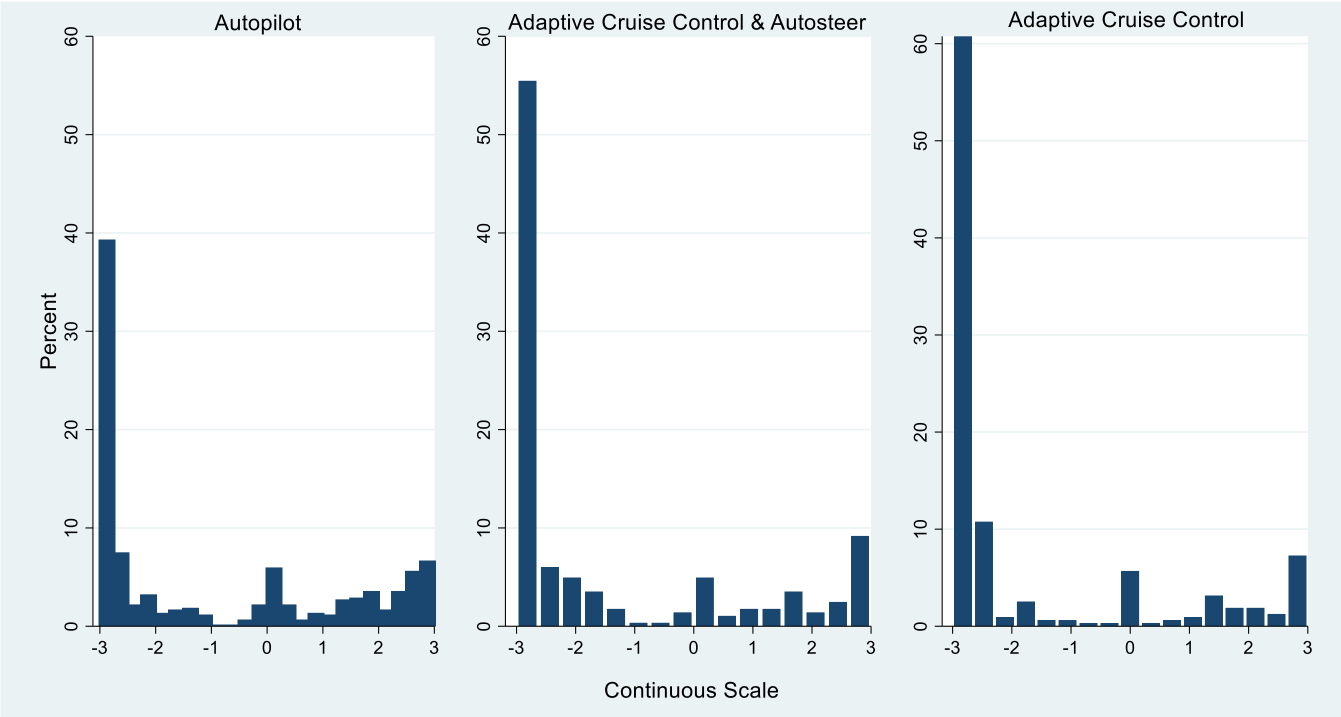

Figure 8. "If for some reason you were no longer able to use [insert automation type] how likely would you be to do the following: Change the time you drive to avoid congestion?" on a continuous scale from Very unlikely (-3) to Very likely (3)

Figure 9 shows respondents are on average very unlikely to choose a different travel mode if they were no longer able to use automation. This may indicate that automation does not substantially influence mode choice. There is no significant difference between any of the three automation systems (Table 7).

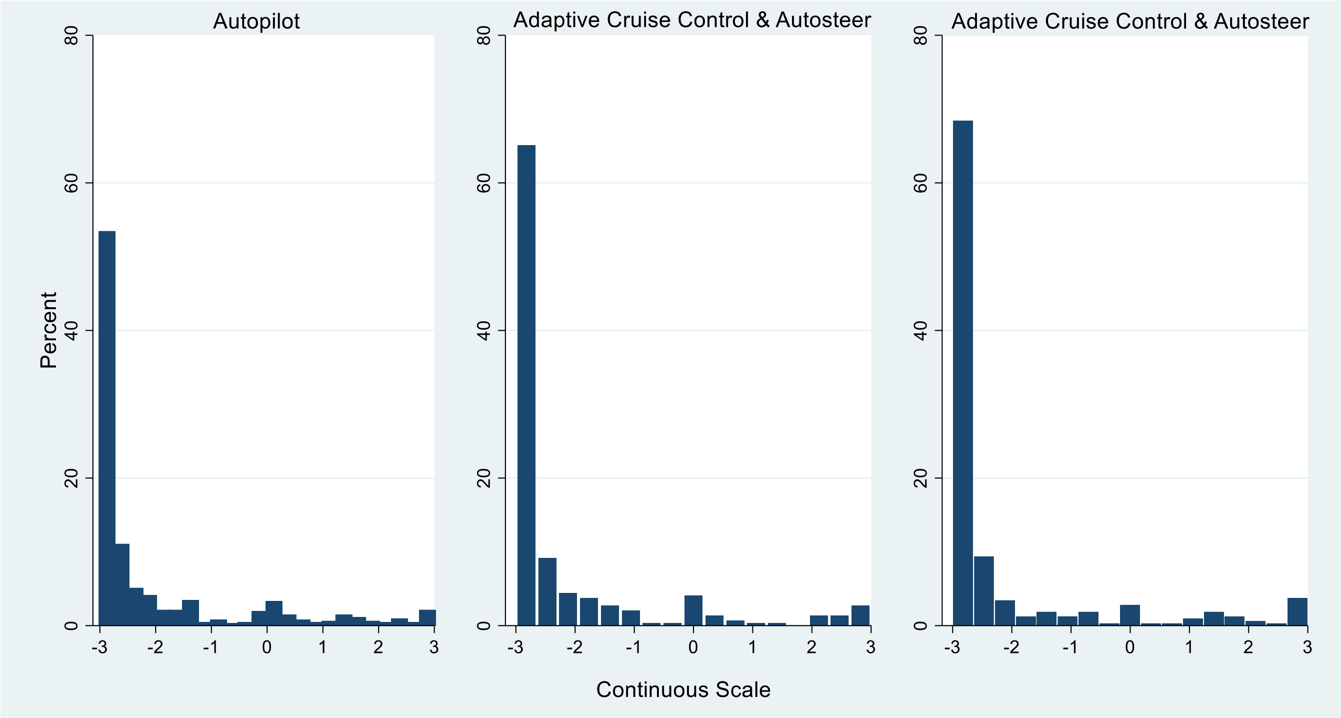

Figure 9. “If for some reason you were no longer able to use [insert automation type] how likely would you be to do the following: Choose different travel modes? (e.g., transit, bike, walk, etc.)” on a continuous scale from Very unlikely (-3) to Very likely (3).

Figure 10 shows respondents' likelihood to change the route they take to avoid congestion. The mean response to this question is higher than any other hypothetical changes: 40.2 percent of Autopilot, 30.2 percent of adaptive cruise control and autosteer, and 27.1 percent of adaptive cruise control only users are likely to change the routes they take to avoid driving in congestion. This supports the results in Figure 7 indicating that automation has an impact on drivers’ decision to drive in congestion both by time of day and the routes they take.

The statistical comparisons in Table 7 show that Autopilot users are significantly more likely to indicate they would do this than users of other automation systems. They also show statistically significant differences between Autopilot and the other driving systems. However, no significant difference was found between responses by users of adaptive cruise control and autosteer and the users of adaptive cruise control only.

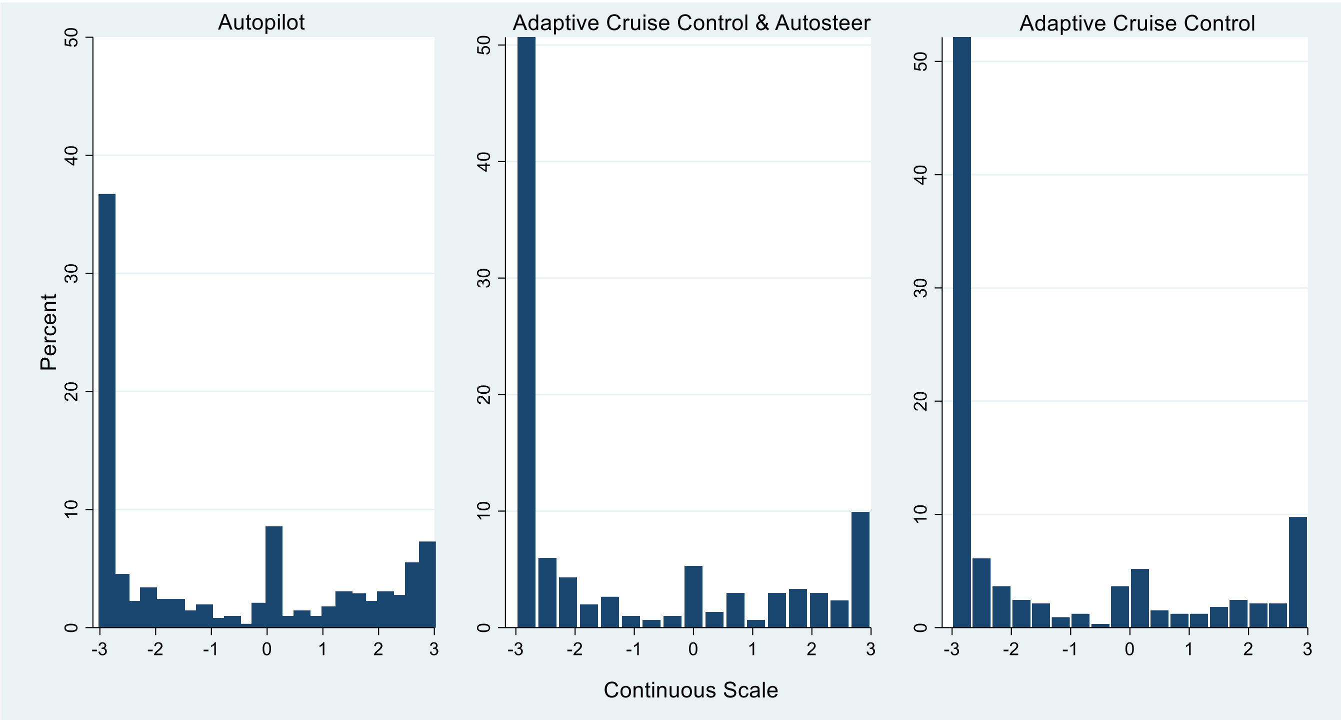

Figure 10. "If for some reason you were no longer able to use [insert automation type] how likely would you be to do the following: Change the routes you take to avoid driving in congestion?" on a continuous scale from Very unlikely (-3) to Very likely (3).

Figure 11 shows on average respondents are "unlikely" to reduce the number of local trips if automation features were no longer available. Partial automation appears to have a lesser effect on the number of local trips than on other travel decisions. Table 7 shows no statistical differences on the impact of automation on local trips for any of the three automation types.

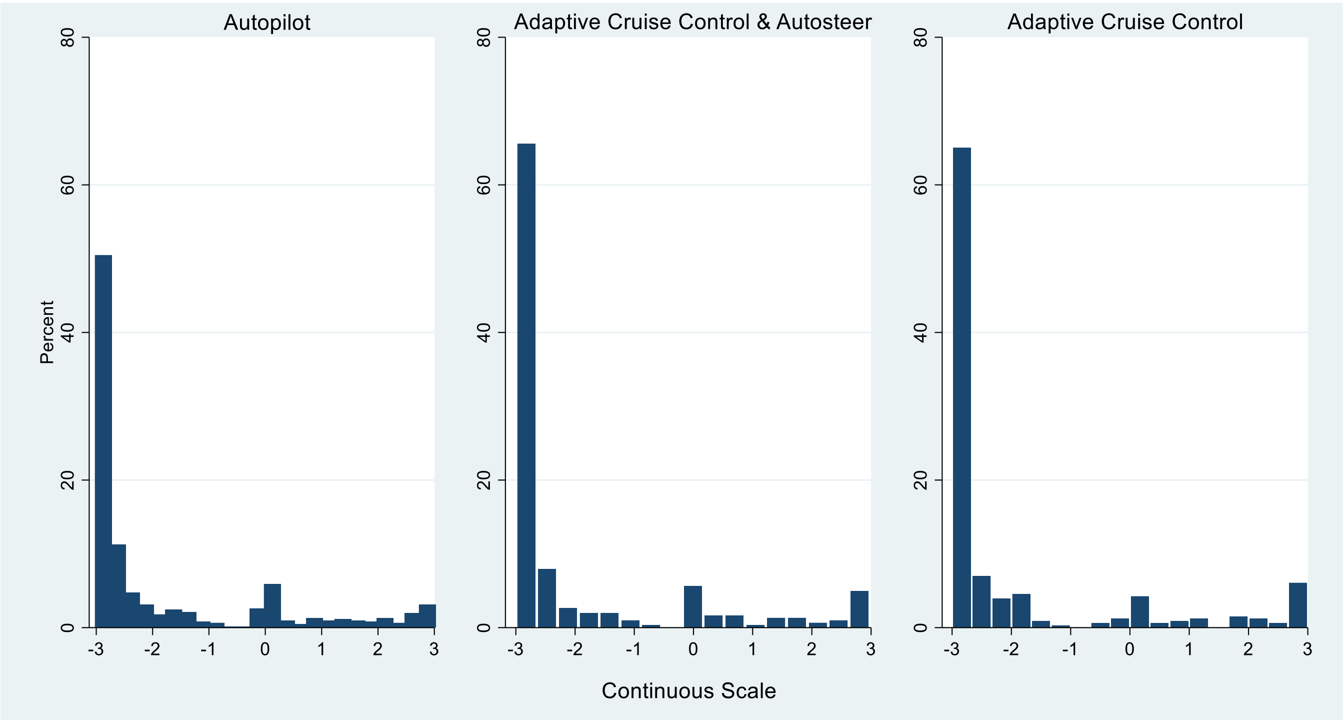

Figure 11. "If for some reason you were no longer able to use [insert automation type] how likely would you be to do the following: Reduce the number of local trips you take?" on a continuous scale from Very unlikely (-3) to Very likely (3)

Figure 12 shows 31.4 percent of Autopilot users, 22.3 percent of adaptive cruise control and autosteer users, and 17.6 percent of adaptive cruise control users indicate they are likely to reduce the number of long-distance trips they take if they could not use vehicle automation. Table 7 shows that there is no significant difference between adaptive cruise control and autosteer and adaptive cruise control only. A significant difference was found when comparing Autopilot to both other automation systems; this indicates that Autopilot may have a greater impact on drivers' decisions to do long distance trips than for other Level 2 automated systems.

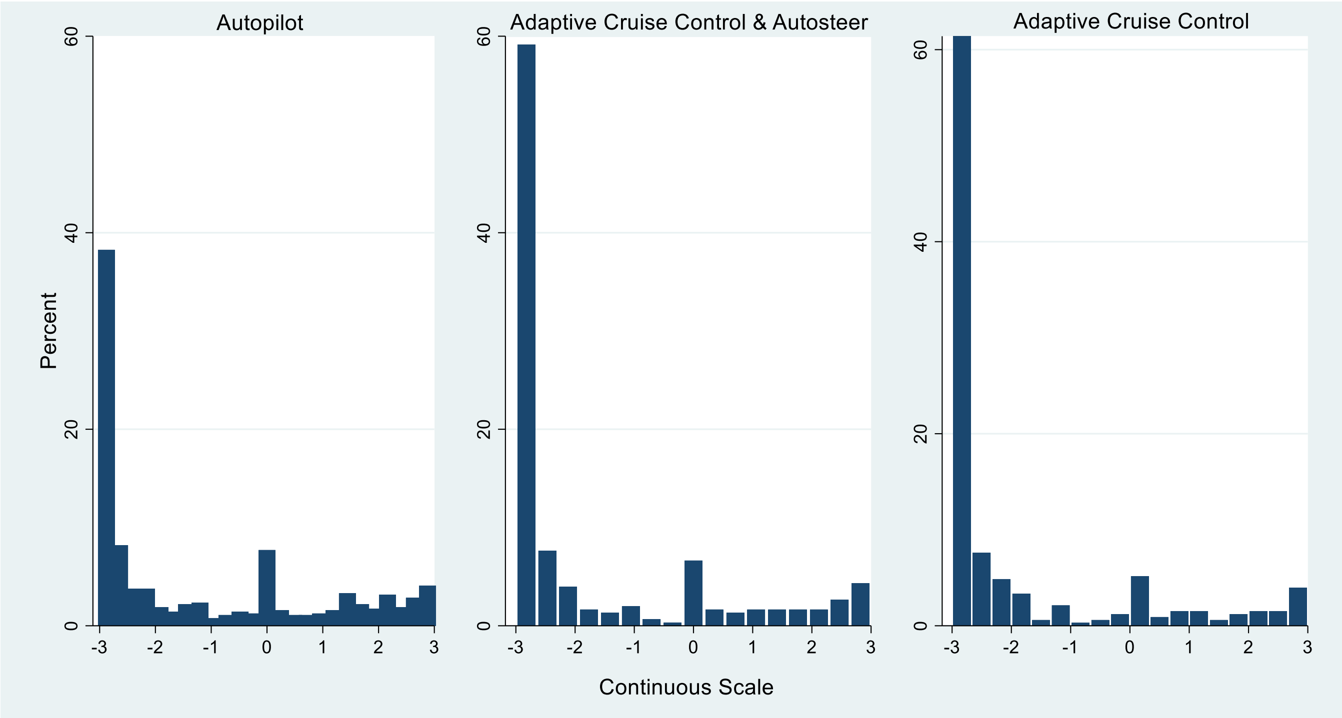

Figure 12. “If for some reason you were no longer able to use [insert automation type] how likely would you be to do the following: Reduce the number of long-distance trips you take?” on a continuous scale from Very unlikely (-3) to Very likely (3)

Figure 13 shows that most users of all three automation systems are very unlikely to share a ride if they no longer had access to their automation system. A greater percentage of drivers with adaptive cruise control and autosteer and adaptive cruise control only stated they are very unlikely to start ride sharing compared to users of Autopilot. However no statistically significant difference was found between any of the three automation systems.

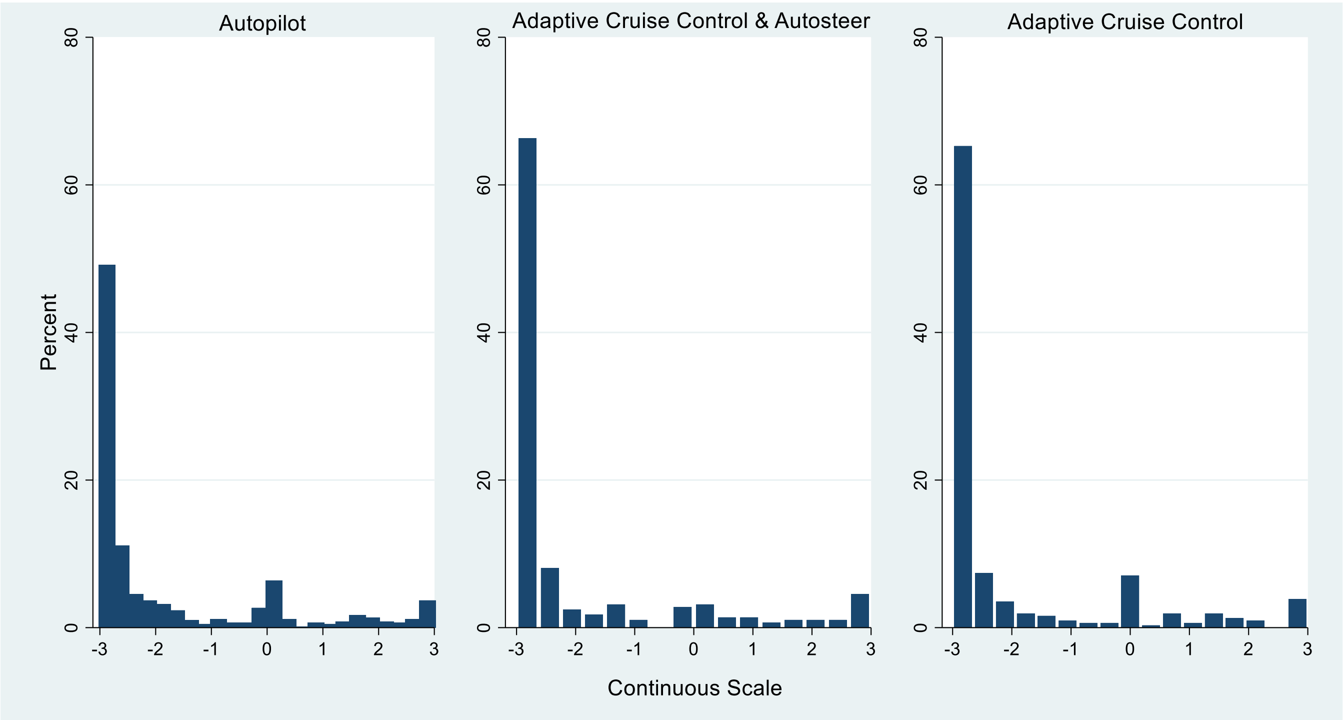

Figure 13. "If for some reason you were no longer able to use [insert automation type] how likely would you be to do the following: Share a ride?" on a continuous scale from Very unlikely (-3) to Very likely (3)

Table 7. Tukey test for pairwise comparison of means for respondents' reported likelihood to change travel if they could not use the automated system. Significant values are red.

	Automation Type	Mean	Auto Levels Comparison	Contrast	Std. Err.	P>|t|
Change Time of Commute to Avoid Congestion	Autopilot	-0.92	Adaptive Cruise Control & Autosteer vs Autopilot	-0.576	0.155	0.001
	Adaptive Cruise Control & Autosteer	-1.50	Adaptive Cruise Control vs Autopilot	-0.838	0.149	<0.001
	Adaptive Cruise Control	-1.76	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-0.262	0.175	0.293
Use Different Travel Mode	Autopilot	-2.04	Adaptive Cruise Control & Autosteer vs Autopilot	-0.147	0.108	0.367
	Adaptive Cruise Control & Autosteer	-2.19	Adaptive Cruise Control vs Autopilot	-0.148	0.105	0.338
	Adaptive Cruise Control	-2.19	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-0.002	0.123	1.000
Change Route to Avoid Congestion	Autopilot	-0.81	Adaptive Cruise Control & Autosteer vs Autopilot	-0.47	0.153	0.006
	Adaptive Cruise Control & Autosteer	-1.28	Adaptive Cruise Control vs Autopilot	-0.574	0.149	<0.001
	Adaptive Cruise Control	-1.38	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-0.104	0.174	0.821
Reduce Number of Local Trips	Autopilot	-1.83	Adaptive Cruise Control & Autosteer vs Autopilot	-0.185	0.122	0.287
	Adaptive Cruise Control & Autosteer	-2.01	Adaptive Cruise Control vs Autopilot	-0.171	0.119	0.323
	Adaptive Cruise Control	-2.00	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	0.014	0.138	0.994
Reduce Number of Long-Distance Trips	Autopilot	-1.20	Adaptive Cruise Control & Autosteer vs Autopilot	-0.566	0.134	<0.001
	Adaptive Cruise Control & Autosteer	-1.76	Adaptive Cruise Control vs Autopilot	-0.738	0.13	<0.001
	Adaptive Cruise Control	-1.94	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	-0.172	0.153	0.498

	Automation Type	Mean	Auto Levels Comparison	Contrast	Std. Err.	P>|t|
Share a Ride	Autopilot	-1.82	Adaptive Cruise Control & Autosteer vs Autopilot	-0.234	0.122	0.133
	Adaptive Cruise Control & Autosteer	-2.05	Adaptive Cruise Control vs Autopilot	-0.225	0.118	0.140
	Adaptive Cruise Control	-2.04	Adaptive Cruise Control vs Adaptive Cruise Control & Autosteer	0.01	0.139	0.997

Summary of Descriptive Data

Overall Autopilot users report using automation more than users of adaptive cruise control and autosteer, and the latter report using automation more than users of only adaptive cruise control. Respondents report being most likely to use automation on freeways, in clear weather, and when traffic levels are low. There is significant divergence in reported use of the systems in different road, traffic, and weather scenarios. The largest difference is in Autopilot users reporting they are significantly more likely to use their system at night and in stop and go traffic. In investigating the impact of adaptive cruise control, adaptive cruise control and autosteer, and Autopilot on travel the largest impacts are on long distance travel and driving in congestion. The results suggest that having these systems causes some drivers to drive their vehicle at congested times of the day and on congested roads, and undertake more long-distance travel, compared to if they did not have automation. Users of Autopilot are the most likely to report this, followed by users of adaptive cruise control and autosteer, with users of adaptive cruise control only being the least likely to report these changes.

Modeling Results

We also directly asked respondents whether automation had led to a change in their local or long-distance travel. Figure 14 shows responses to this question. For local travel, two percent of adaptive cruise control only users, five percent of adaptive cruise control and autosteer users, and 10 percent of Autopilot users indicated the automation systems led to them doing more local travel. The majority report no change to their local travel. For long distance travel 15 percent of adaptive cruise control only users, 21 percent of adaptive cruise control and autosteer users, and 36 percent of Autopilot users reported doing more long-distance travel. Users of Tesla Autopilot reported doing more long-distance travel due to automation than users of adaptive cruise control only and adaptive cruise control and autosteer. Few respondents reported less local or long-distance travel.

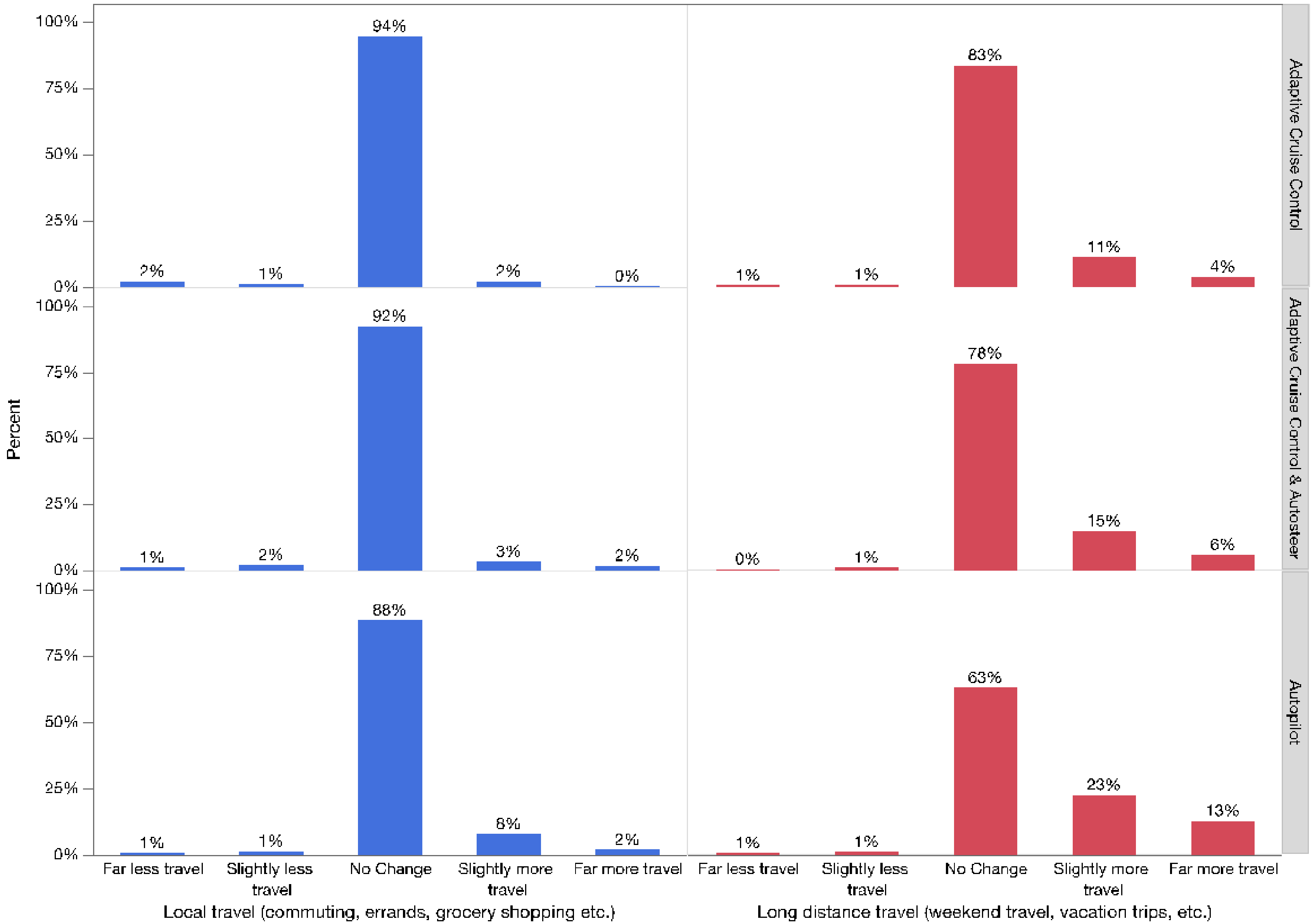

Figure 14. Reported changes to local travel (left column) and long-distance travel (right column) for those with Adaptive Cruise Control (top row), adaptive cruise control and autosteer (middle row), and Autopilot (bottom row)

Long Distance Travel Changes

To understand factors related to reported increases in long-distance travel because of automation we use a binary logistic regression model with self-reported changes to travel as the dependent variable. We focus on long distance travel, since this is where the majority of increases were reported by respondents. The dependent variable in this model is a binary variable taken from answers in Figure 14. If respondents reported slightly more or far more long-distance travel, they are assigned a value of 1, if they did not report any more travel, they are assigned a value of 0. Table 8 shows the results of the model for those with any Level 2 automation system (Autopilot users and users of adaptive cruise control and autosteer), Table 9 shows the results for the model with those who have a Tesla with Autopilot. The tables include odds ratios for the independent variables.

The results of the model for all Level 2 automation types (Table 8) shows that reporting an increase in travel due to automation is correlated with household Income, the attitudinal factor "Commuting in congestion, stressful commute," the automation user factors "Empty roads, clear weather, freeway," "Any weather," "Slow traffic," and "All roads."

Lower household incomes are correlated with reporting an increase in travel. The attitudinal and lifestyle factor "Commuting in congestion, stressful commute" is also negatively correlated. This could be explained by drivers being less motivated to undertake more long distance travel on the weekend because of a desire to not drive due to the stress associated from driving their vehicle to work. Those who do not have a stressful commute may be more willing to undertake additional long-distance travel on the weekends.

The automation user factors "Empty roads, clear weather, freeway," "Any weather," "Slow traffic," and "All roads" are all positively correlated with reporting more long-distance travel as a result of automation. This indicates those who use automation on a wider variety of roads, weather, and traffic conditions are more likely to report travelling more due to automation. This could be because those who are more comfortable or confident in using Level 2 automation are more likely to report travelling more, perhaps because they can rely on the system for a larger portion of their journeys which may alleviate some of the fatigue associate with long distance travel.

Table 8. Binary logistic regression model results for reported increases to long-distance travel as a result of automation for drivers of all vehicle types with Level 2 automation. Significant values are shown in red.

Term		Odds Ratio	Standard Error	Prob>ChiSq
Age		0.991	0.0065	0.1446
Gender (1 male, 0 other)		0.881	0.1989	0.5736
Household Income		0.998	0.0007	0.0126*
Home type (detached 1, other 0)		0.837	0.1976	0.4503
Education ordinal		0.966	0.1162	0.7753
Free charging (1 free, 0 no free charging)		1.161	0.1900	0.3612
Commuting in congestion, stressful commute		0.822	0.0774	0.0372*
Outdoor lifestyle		1.099	0.0998	0.3002
Empty roads, clear weather, freeway		1.717	0.2261	<0.001*
Any weather		1.219	0.1060	0.0229*
Slow traffic		1.295	0.1257	0.0077*
All roads		1.442	0.1439	<0.001*
Pro technology		1.172	0.1416	0.1899
Household People		1.020	0.0756	0.7866
Oneway commute distance		1.002	0.0041	0.6216
RSquare (U)			0.0793	
-LogLikelihood			463.00563	
Observations (or Sum Wgts)			814	

Note: The binary dependent variable is: 1 = more long-distance travel due to automation, 0 = no increase in long distance travel.

Since there may be considerable variation in the performance of Level 2 automated systems between vehicles from different automakers which would be difficult to control for, we run a model with only users of Tesla Autopilot. This allows us to investigate the impact of automation in an environment where differences between automated systems are not an issue in the sample. The results of this model are shown in Table 9. The model shows age, household income, the attitudinal factors “Commuting in congestion, stressful commute,” “Outdoor lifestyle,” and the automation user factors “Empty roads, clear weather, freeway,” “Any weather,” and “All roads” are correlated with reporting more long-distance travel due to automation.

Age is negatively correlated, indicating that the lower the driver’s age the higher the odds of reporting more long-distance travel. This suggests Autopilot induces travel among younger Tesla owners. As with the model with all Level 2 automation, users’ income is negatively correlated. The attitudinal factor “Commuting in congestion, stressful commute” is negatively correlated, a one unit increase in this factor results in 30 percent lower odds of reporting an increase in travel due to using Autopilot. Again, we believe this to be because those with a stressful commute are less likely to want to undertake additional travel. In this model the attitudinal factor “Outdoor lifestyle” is positively correlated, a one unit increase in this factor results in 25.7 percent higher odds of reporting more long-distance travel. This could be explained by those who desire to spent time outdoors wanting to travel more to outdoor destinations and Autopilot facilitating this. The automation user factors “Empty roads, clear weather, freeway,” “Any weather,” and “All roads” are all positively corelated. Those who report using automation in a greater variety of conditions have higher odds of reporting an increase to their travel.

Table 9. Binary logistic regression model results for reported increases to long-distance travel as a result of Autopilot for Tesla owners with Autopilot only. Significant values are shown in red.

Term	Odds Ratio	Standard Error	Prob>ChiSq
Intercept			0.1991
Age	0.981311	0.008078839	0.0219*
Gender (1 male, 0 other)	0.892738	0.271111229	0.7087
Household Income	0.997994	0.000808974	0.0132*
Home type (detached 1, other 0)	0.899467	0.279227837	0.7329
Education ordinal	0.942759	0.141768422	0.6951
Free charging (1 free, 0 no free charging)	1.084943	0.218540502	0.6857
Commuting in congestion, stressful commute	0.700844	0.084356527	0.0031*
Outdoor lifestyle	1.256951	0.141151072	0.0417*
Empty roads, clear weather, freeway	1.870136	0.347199538	<0.001*
Any weather	1.291967	0.145246677	0.0227*
Slow traffic	1.127713	0.193802779	0.4843
All roads	1.781124	0.22683095	<0.001*
Pro technology	0.987704	0.150339018	0.9352
Household People	1.000089	0.089999309	0.9992
Oneway commute distance	1.004469	0.005059209	0.376
RSquare (U)		0.1206	
-LogLikelihood		306.84506	
Observations (or Sum Wgts)		533	

Note: The binary dependent variable is: 1 = more long-distance travel due to automation, 0 = no increase in long distance travel.

Propensity Score Matching Analysis

In these models we only investigated the impact of Autopilot on VMT of Tesla drivers. We chose this subset of PEV owners to prevent the risk that outside factors specific to the decision to choose different vehicles would influence the results of the model. For example, we hypothesize that a Tesla owner without Autopilot is more similar to a Tesla owner with Autopilot than an owner of a PEV from a different vehicle make. By investigating only Tesla owners we compare two groups who own effectively the same PEV, but one has automation and the other does not. Also, both the owners of a Tesla with Autopilot and the owners of a Tesla without Autopilot have similar range and access to Tesla's supercharger network.

Table 10 presents the model results with average treatment effects. The table shows that if all Tesla owners had Autopilot the average VMT would be 4884 miles more than if no Tesla owners had autopilot. The results in this model are statistically significant. For the final model specification described here, the number of neighbors chosen for matching is two. The choice of the number of neighbors depends on the tradeoff between bias and efficiency. Though a higher number of neighbors may give more efficient estimates, it can also introduce bias by matching observations that are not very similar. Though we tried models with three and four neighbors, the two-neighbor model was chosen keeping in mind the trade-off and was based on the covariate balance test after the matching process was completed.

The results in Table 11 show the result for average treatment effect on the treated. The results suggest that after controlling for all the baseline characteristics, the average VMT is 4680 miles higher for Tesla owners when they have Autopilot than when they do not. However, the results in this model are not statistically significant.

Table 10. Estimate of Average Increase in VMT for Tesla owners with Autopilot (PSM with 2 neighbors)

Treatment-effects estimation (ATE)		Number of obs	=	724		
Estimator: propensity-score matching		Matches: requested	=	2		
Outcome model: matching		min	=	2		
Treatment model: logit		max	=	2		
Outcome: VMT	Coef.	AI Robust Std. Err.	z	P>z	[95%Conf.	Interval]
Tesla Autopilot (1 vs 0)	**4883.762**	**2282.312**	**2.14**	**0.032**	**410.5122**	**9357.011**

Table 11. Estimate of Average Increase in VMT for Tesla owners with Autopilot (PSM with 2 neighbors)

Treatment-effects estimation (ATT)		Number of obs	=	724		
Estimator: propensity-score matching		Matches: requested	=	2		
Outcome model: matching		min	=	2		
Treatment model: logit		max	=	2		
Outcome: VMT	Coef.	Std. Err.	z	P>z	[95%Conf.	Interval]
Tesla Autopilot (1 vs 0)	**4679.933**	**2961.636**	**1.58**	**0.114**	**-1124.77**	**10484.63**

As the validity of the estimates derived from PSM analysis is dependent on the assumptions of conditional independence and the assumption of common support/overlap, we check whether our model specification meets these assumptions.

Covariates are balanced and the conditional independence assumption is satisfied when the distribution of the covariates do not vary over treatment levels. To check the conditional independence assumption, we consider the standardized difference in mean between the treated and untreated group and the variance ratio of the covariates for the raw and the matched sample [63]. When the value of the difference in mean in the matched sample is closer to zero and the variance ratio is closer to 1, the covariate is said to be balanced.

Table 12 gives the covariance balance summary for the final model specification. The covariate balance summary is also represented using a box plot in Figure 15.

Table 12. Covariate balance summary

	Standardized Differences		Variance ratio	
	Raw	Matched	Raw	Matched
Neighborhood type (base: Urban)				
Suburban	0.18	0.03	1.49	1.06
Rural in Urban	0.01	-0.14	1.00	1.03
Rural	-0.06	0.10	0.89	1.21
Commute Distance	-0.06	-0.02	0.70	0.87
Lifestyle factor: Unpleasant commute	0.25	-0.05	1.03	1.09
Lifestyle factor: Likes suburban living	0.00	0.04	0.96	0.90
Lifestyle factor: Likes outdoor lifestyle	-0.50	0.03	0.68	0.80
Respondent Age X Lifestyle factor: Pro-technology	0.17	-0.05	0.72	0.83
Age of Primary Driver	-0.10	0.05	1.43	1.26
Household Income	-0.04	-0.04	0.90	0.99
Number of licensed drivers	-0.13	-0.01	0.62	0.69
Number of household vehicles	-0.14	-0.01	0.88	0.95
Vehicle type (SUV=1)	0.14	0.04	1.83	1.19
Whether drivers have access to free charging (e.g., free supercharging)	0.31	0.11	0.65	0.86

The standardized difference in mean between the treated and the untreated observation in the matched sample is close to zero for all the variables except the dummy variable representing membership of Tesla's supercharger network and the neighborhood type categories "Rural-in-Urban" and "Rural." Though the difference in mean is not as close to zero as desired, the variables or potential confounders are retained as they can have an important effect on VMT. Similarly, the variance ratio is close to one for most variables. Two variables, number of licensed drivers, and membership in Tesla's charging network have variance ratios further away from 1 but are retained because they are likely confounders that may affect VMT, choice of Autopilot, or both.

Figure 15 shows the distribution of the covariates in the raw and matched sample over the treatment levels (Autopilot/No Autopilot).

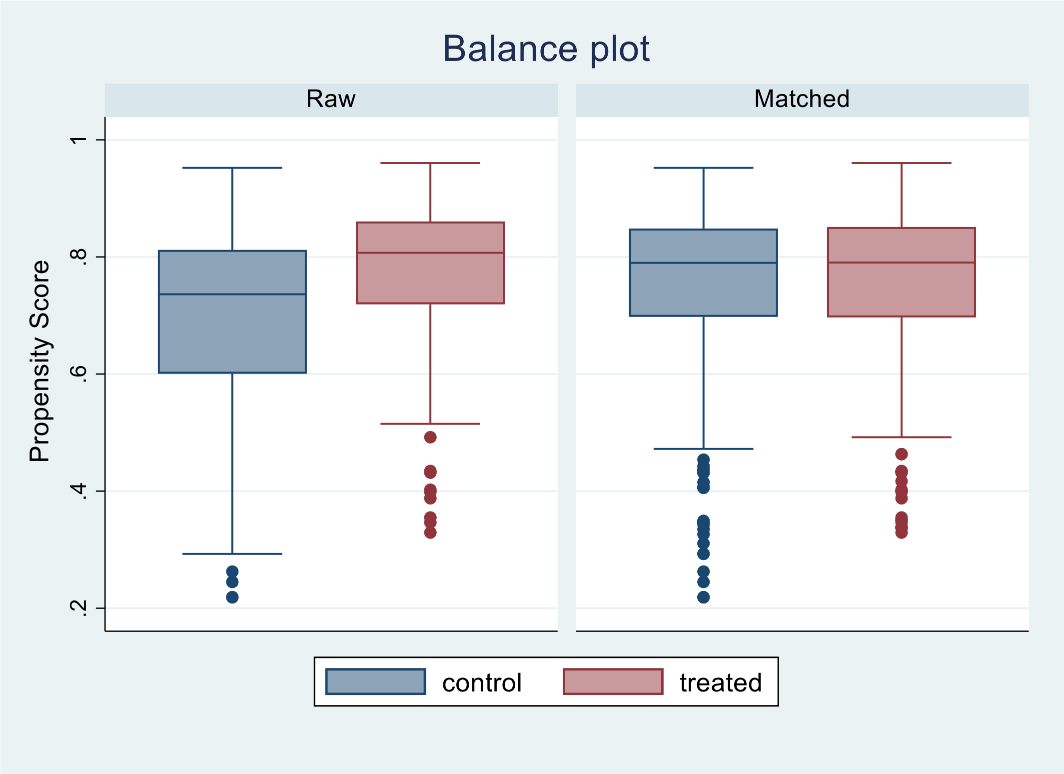

Figure 15. Distribution of the covariates

The medians, the 25th percentiles, and the 75th percentiles appear to be the same, although there are some differences in the tails, the lower adjacent values, and the outliers. Matching on the estimated propensity score appears to have balanced the baseline characteristics for the matched sample except for the tails.

The overlap or common support assumption is said to be satisfied when there is a positive probability of having observations in both the treatment and control groups at each combination of covariate values. Figure 15 shows the distribution of the probability of treatment among the treatment and control group after the matching process.

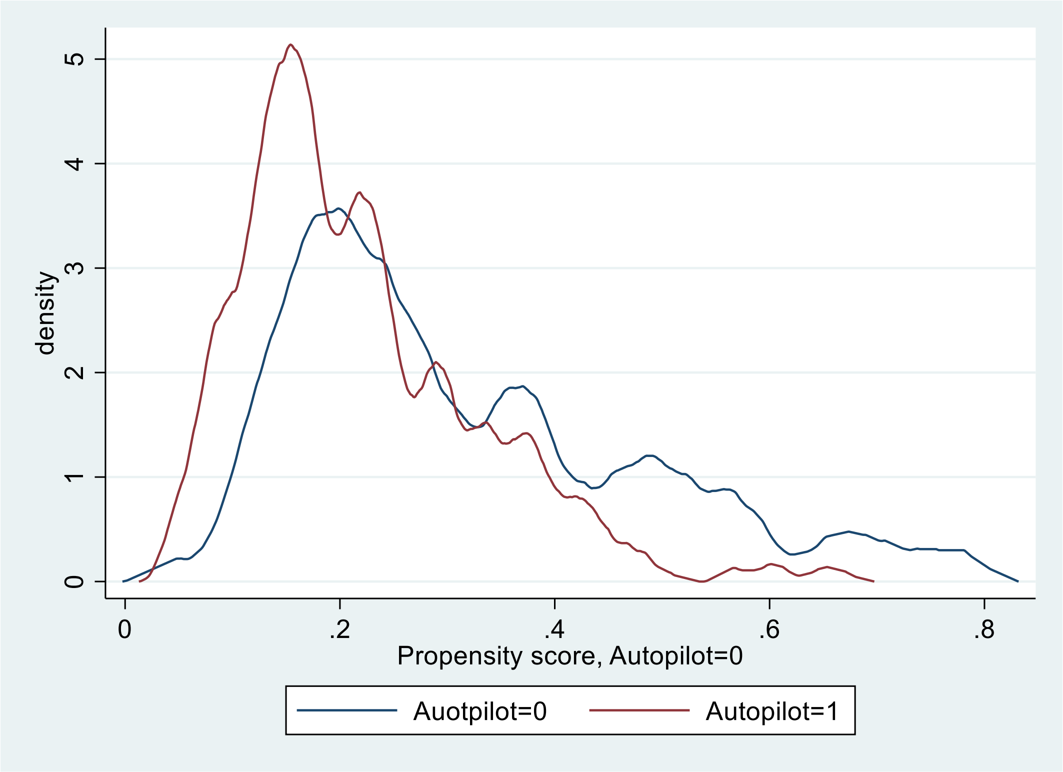

Figure 16. Common support/Overlap condition

The graph in Figure 15 displays the estimated density of the predicted probabilities that a Tesla with no Autopilot does not get the treatment (Autopilot) and the estimated density of the predicted probabilities that a Tesla owner with Autopilot does not get the treatment. We observe that two estimated densities have most of their respective masses in regions in which they overlap each other (except the tails). Thereby, we conclude that with the current model specification there is no evidence that the overlap assumption is violated.

Conclusion

The survey results from users of partially automated PEVs show automation is used on average for 65-70 percent of trips, for 41-47 percent of commute distances, and on around 74 percent of the miles for long-distance trips. Tesla's Autopilot is used significantly more than partially automated systems from other automakers, and is used on a greater variety of roads, and in a greater variety of traffic and weather conditions.

The results suggest that partial automation has a positive impact on drivers' willingness to drive on congested roads, at congested times of the day, and undertake more long-distance travel. Partial automation does not appear to substantially impact local travel demand. Significantly more Autopilot users report that they would seek to avoid congestion if they could not use automation than users of other automated systems, and significantly more reported that they do more long-distance travel in their partially automated vehicle due to automation. Whether these findings are a result of Autopilot being technically different from other automaker's systems, or whether these differences are due to different attitudes of Autopilot users is not clear. It is possible that both have an impact.

We investigated the effect of automation on the decision to undertake more long-distance travel. The result of the model found that drivers who use automation under different road, weather, and traffic conditions are more likely to report more long-distance travel. This may mean the degree to which automation induces more travel depends on how comfortable drivers are in using automation in different environments, with those who have more confidence or trust in the system being more likely to undertake more travel. Drivers who have a stressful commute are *less* likely to report more long-distance travel. These drivers may have no desire to undertake more weekend travel due to the stress associated with daily driving. Income is negatively correlated with reporting more long-distance travel (i.e., as income increases the odds of undertaking more travel decreases). It should be noted, though, that no respondents could be considered low-income (the mean household income for Autopilot users is $210,000 and the mean for users of other automated systems is $167,000). Finally, among Autopilot users those with an outdoor lifestyle report more long-distance travel. This may be because those who desire to visit outside destinations are more motivated to travel longer distances to get to them.

It should be noted that respondents' self-reported decisions to travel more could be affected by their ability to recall their travel patterns prior to owning a partially automated vehicle. To obtain a more accurate view of the impact of automation on VMT, we used propensity score matching to compare the VMT of partially automated vehicles equipped with Autopilot with those that do not have automation. The results indicated that if all Tesla drivers had access to Autopilot, the average VMT would be 4,888 miles more than if none of them had Autopilot. The estimate from this econometric method indicated that partial automation can cause a substantial increase in travel.

Policy Implications

The Federal government and California have both set goals for reducing vehicle miles travelled. These goals are needed in part to meet emissions targets [64, 65]. While the partially automated PEVs in this study do have zero tailpipe emissions they still produce emissions upstream from the production of electricity. This will mean any VMT increase will be accompanied by an increase in emissions. Further, increases to traffic congestion will lead to higher emissions from other vehicles on the roads.

No policies currently exist that could be used to curb any VMT increase in partially automated PEVs. New PEVs sold in California pay a flat $100 fee in addition to their existing registration fees each year for their road use. Owners of PEVs do not pay fuel taxes and at present there is no mileage-based fee that electric vehicles pay. Further, some are discussing whether “off cycle credits” should be awarded to automated vehicles based on their potential to increase vehicle efficiency (e.g., by smoothing traffic flow). Existing technologies that currently receive these credits include: active aerodynamics, engine idle stop, solar panels, among others [66]. Awarding off cycle credits to partially automated vehicles, with the goal of encouraging their introduction due to their potential efficiency improvements may, however, lead to an increase in energy consumption through an increase in VMT.

Future research

We did not investigate the reasons why drivers reported driving more at congested times of the day and on congested roads since it was beyond the scope of this study. This is an important area of future research since such changes could impact congestion especially when more vehicles have partial automation.

The impact of increased long-distance travel, driving more in congestion, and increased VMT on emissions need research attention. The degree to which this will impact federal and state emissions targets is not clear; modelling studies could be used to estimate the emission and energy consumption impact of partial automation.

Future research could also investigate policy interventions that could be used to curb any increase in VMT. One option could be through pricing, for example, a VMT-based fee.

Appendix – Statistical Analysis

Automation User Factors

Factor analysis was used to simplify the survey respondents' answers to multiple questions on travel behavior by grouping them into four different categories based on when and how likely they are to use their vehicle's automation features on different road types, in different driving conditions, and given different traffic levels: These four "user factors" classify respondents' behavior based on a combination of their answers to those questions:[4]

1) **Empty roads, clear weather, freeway**: Respondent is likely to use automation in clear weather, on interstates or freeways, on empty roads, in fast moving traffic, in rain, or at night.
2) **Any weather**: Respondent is likely to use automation in fog, snow, rain, and at night.
3) **Slow traffic**: Respondent is likely to use automation in stop and go traffic and slow-moving traffic.
4) **All roads**: Respondent is likely to use automation on urban roads, rural roads, on/off-ramps of interstates, freeways, or highways, parking lots

Table 13 shows how these factors were constructed from the 13 scenarios in which respondents indicated how likely they are to use vehicle automation. The numbers, or "factor loadings" show how strongly or weakly a positive response to each question contributes to the responses being placed in one or another classification.

[4] The optimal number of factors was four, which account for 72.5 percent of the variance in the data; additional factors only result in a negligible increase in the variation explained.

Table 13. Factor loadings for the four Autopilot user factors, and 13 scenarios in which respondents were asked how likely they were to use automation.

When automation used	Empty roads, clear weather, freeway	Any weather	Slow traffic	All roads
Clear weather	0.844048	0.092121	0.130114	0.066484
Interstate or Freeway	0.77053	0.130489	0.14389	0.180403
Empty road	0.730707	0.069187	0.042211	0.028755
Fast moving traffic	0.622192	0.276394	0.109943	0.095356
Fog	0.153575	0.85706	0.181361	0.195198
Snow	0.057487	0.720606	0.146181	0.24391
Rain	0.3453	0.710607	0.181155	0.18716
Night	0.500687	0.505977	0.257051	0.156204
Stop and go traffic	0.14277	0.233902	0.94871	0.15766
Slow moving traffic	0.272647	0.265728	0.733805	0.216083
Urban Roads	0.168566	0.109687	0.083534	0.732272
Rural Roads	0.226319	0.100803	-0.020261	0.563232
On/off-ramps of interstates, freeways, or highways	0.074441	0.214126	0.170312	0.490055
Parking Lots	-0.072529	0.09069	0.094198	0.350029

Attitudinal and Lifestyle Factors

Personal attitudes and lifestyle are closely related to travel behavior [49–56], therefore the model includes attitudinal and lifestyle factors to explain reported changes to travel as a result of using a partially automated vehicle. The eight factors listed below were constructed based on answers to 22 questions in the survey:

1) **Commuting in congestion, stressful commute**: Having the belief that commuting is stressful, traffic congestion is a problem, that commuting is time wasted, and disagreeing that their commute is pleasant.
2) **Like Suburban Living**: Wanting to live in a spacious house, liking the idea of a large yard and plenty of space between houses, and not desiring to live near transit.
3) **Outdoor lifestyle**: Enjoying having an outdoor lifestyle and travelling to outdoor destinations.
4) **Enjoy shopping in stores**: Preferring shopping in stores rather than shopping online.
5) **Exercise not important**: Belief that exercise isn't important and the importance of it is overrated.
6) **Pro-technology**: Liking to be among the first to have the latest technology and liking to try new and different things.
7) **Having children means need a car, like routine**: Belief that having children means you need a car and liking sticking to a routine.
8) **Congestion is a problem, try to make use of travel time**: Believing traffic congestion is a problem and trying to make the best use of time spent travelling.

Table 14 shows the factor loadings for each of the 22 questions

Table 14. Table Showing Factor Analysis of Lifestyle/Attitudinal Statements and The Factor Loading for Each of the 8 Factors.

	Commuting in congestion, stressful commute	Like suburban living	Outdoor lifestyle	Enjoy shopping in stores	Exercise not important	Pro-technology	Having children means need a car, like routine	Congestion is a problem, try to make use of travel time
My commute is stressful	0.83348	-0.0519	0.02196	0.03888	0.0576	0.02317	0.07077	0.01798
Traffic congestion is a major problem for me personally	0.49319	0.06928	-0.06488	0.02396	-0.01411	0.04877	-0.00388	0.42235
The time I spend commuting is generally wasted time	0.3725	0.00017	0.02328	-0.02198	0.04684	0.03364	0.01694	0.02506
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to	-0.00666	0.82748	0.00547	0.03537	0.0459	0.05865	-0.00771	0.0881
I like the idea of living somewhere with large yards and lots of space between homes	-0.01719	0.6663	0.09852	-0.03523	0.01654	-0.01253	0.0479	0.14978
Most of the time, I have no reasonable alternative to driving	0.12417	0.24898	-0.02149	0.02938	0.02954	0.05351	0.20694	-0.11559
I enjoy having an outdoor lifestyle (such as hiking, camping, winter sports, water sports)	0.00449	0.01745	0.87262	-0.04823	-0.02503	-0.03247	-0.04872	0.05037
I like traveling to visit outdoor destinations (e.g., National and State Parks)	0.02504	0.01973	0.63988	0.00697	-0.00329	-0.00753	-0.03406	-0.04781
Getting regular exercise is very important to me	-0.0422	-0.1054	0.23794	0.04292	-0.45149	0.02836	0.14923	0.0969

	Commuting in congestion, stressful commute	Like suburban living	Outdoor lifestyle	Enjoy shopping in stores	Exercise not important	Pro-technology	Having children means need a car, like routine	Congestion is a problem, try to make use of travel time
I prefer to shop in a store rather than online	-0.01402	-0.05223	-0.03595	1.0266	-0.04466	0.07791	0.04686	0.01044
Technology creates at least as many problems as it does solutions	0.07469	-0.00679	0.05432	0.14324	0.10473	-0.27893	0.04826	0.11188
The importance of exercise is overrated	0.01271	-0.0308	0.034	-0.02527	0.96712	-0.01806	0.05273	0.05462
Getting stuck in traffic does not bother me that much	-0.25232	-0.01179	0.02733	0.04968	0.15241	0.10741	0.0068	-0.12001
I like to be among the first people to have the latest technology	0.03213	0.01294	-0.09125	0.00081	0.07193	0.738	-0.03668	0.09533
I like trying things that are new and different	0.03386	-0.01695	0.11633	0.02521	-0.02938	0.57929	0.01336	0.07415
Having children means you have to have a car	0.01762	0.04769	0.01098	-0.02393	-0.02249	0.01121	0.4534	-0.06276
I like sticking to a routine	-0.02121	-0.04238	-0.06238	-0.02338	0.00919	-0.08891	0.45182	0.11621
I definitely want to own a car	-0.03411	0.22275	0.01312	0.05912	-0.0174	0.08484	0.2998	-0.09485
I enjoy shopping online	0.03921	-0.03563	0.00212	-0.39324	0.02083	0.2012	0.27752	0.04665
I try to make good use of the time I spend traveling	-0.039	-0.00401	0.10854	-0.01059	-0.04056	0.13215	0.04661	0.39875
My commute is generally pleasant	-0.80474	0.0327	-0.00738	-0.00195	0.03766	0.03131	0.09822	0.29902
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area	0.05348	-0.73675	0.067	0.05023	0.03824	0.08697	0.06127	0.12483

Binary Logistic Regression

To understand changes to travel behavior from driving a vehicle with Level 2 automation and Autopilot we employed a direct questioning approach [27] using the question from the survey that asks "Please indicate how you think the following has changed as a result of [automationtype]" for Local Travel and Long-distance Travel. We use a binary logistic regression model to identify the independent variables (descriptive statistics, automation user, and lifestyle/attitudinal factors) listed below that would result in the participants reporting "slightly more travel" or "far more travel" for long-distance trips. We focus on long distance travel as substantially more respondents report this as a change they have experienced. We acknowledge that self-reported questions on travel behavior changes have limitations, specifically because we cannot quantify increases in travel, but we believe the results are still interesting and relevant. The model contains the following variables:

Descriptive Statistics

- Age
- Gender (1 male, 0 other)
- Household Income
- Home type (detached 1, other 0)
- Education ordinal Free charging (1 free, 0 no free charging)
- Household people
- One-way commute distance

Automation User Factors

- Empty roads, clear weather, freeway
- Any weather
- Slow traffic
- All roads

Lifestyle/Attitudinal Factors

- Commuting in congestion, stressful commute
- Outdoor lifestyle
- Pro technology

We removed the following descriptive variables due to collinearity: number of people in the household since it is correlated with age and vehicles in household and annual VMT since it is correlated with commute distance, we remove home ownership since it is correlated with home type. We only retain only three lifestyle factors due to the same issue.

In the model with all survey respondents with Level 2 automation model we remove five outliers, and in the model with only Tesla Autopilot users we removed two outliers.

Propensity Score Matching

Our propensity score matching focused on Tesla BEVs. Our focus is on these vehicles because they are the most common partially automated BEVs on the roads today which made obtaining a large sample for analysis possible. autosteer, autopark, lane assist, collision avoidance assist, and speed assist [57]. Further by investigating only one type of vehicle automation the analysis is not complicated by potential differences in level 2 vehicle automation types, or differences between electric vehicles that could impact drivers' decisions.

In this section we describe the method used to conduct a quantitative analysis of the effect of partial automation (also referred to as Level 2 automation) technology on vehicle miles traveled (VMT). Generally, it is a challenge to determine the causal effect of any vehicle characteristic like fuel economy or automation technology on VMT due to self-selection issues i.e., baseline characteristics of vehicle owners that may influence the choice of the vehicle characteristic. Ideally in an experimental setup such as a randomized control trial (RCT), the choice of the vehicle characteristic would be random in the population of vehicle owners [58]. Considering partial automation as a treatment, in a RCT the only difference between the treated and the untreated owners would be the presence or absence of the automation technology in the vehicle. In this scenario, as the treatment status is not confounded by either measured or unmeasured characteristics of the study units, the average of the difference in outcome of the treated and untreated vehicle owners represents the causal effect of the treatment. In a non-experimental setting such as with the data we have here, the choice of treatment or partial automation is often influenced by characteristics of the vehicle owners like their attitude towards technology, residential location, commuting patterns, or lifestyle choice like preference for long-distance road trips. To estimate the causal effect in a non-experimental setting, we need to account for such systematic differences in baseline characteristics between treated and untreated units[58, 59].

In this study, we use propensity score matching (PSM) whereby the outcome (VMT) of plug-in electric vehicle (PEV) owners is compared to evaluate the impact of the treatment (partial automation) accounting for differences in the characteristics of the PEV owners. There are three main steps in the estimation of the impact of partial automation on VMT. First, we estimate the propensity score or the probability of treatment assignment conditional on observed baseline characteristics. Since it can be hard to determine similarity among individuals based on multiple observable characteristics, the propensity score is estimated so that similarity can be defined based on a single metric. Propensity score is a balancing score such that rather than matching on all values of the observed characteristics, individual units can be compared based on their propensity scores alone [58, 60, 61]. The propensity score is calculated here using logistic regression with the status of treatment as the dependent variable and the observable characteristics of the individuals as the covariates. then, after the propensity score is estimated, PSM entails forming matched sets of treated and untreated subjects who share a similar value of the propensity score. We choose the n-nearest neighbor matching algorithm (with replacement) to evaluate the estimated propensity scores and match the untreated individuals (without partial automation) to treated units (with partial automation) with the lowest score difference. The choice of "n" in n-nearest neighbor is based on the trade-off between bias and efficiency in the matching process. By choosing only one nearest neighbor, selection bias can be minimized by using the most similar observation. However, a great deal of information is missed while matching with only one individual potentially yielding less efficient estimates [62]. Finally, we estimate the impact of the treatment using the matched sample and calculate standard errors. The impact of partial automation technology on VMT is measured by computing two parameters: the average treatment effect (ATE) and the average treatment effect on the treated (ATT) [58].

Considering Y_1 as the VMT the PEV owners with partial automation, Y_0 as the VMT of PEV owners with no partial automation, and T as the treatment or a vehicle with the partial automation technology, the average treatment effect is given as $ATE = E[Y_1 - Y_0]$= $E[Y_1]$- $E[Y_0]$. It represents the average effect at the population level of moving all PEV owners to vehicles with partial automation.

The average treatment effect on the treated is given as ATT=$E[Y_1 - Y_0|T = 1]$. It represents the average effect of partial automation on the VMT of the PEV owners with the automation technology.

One of the crucial assumptions of the PSM method is that the set of covariates used in estimating the propensity score should include all the characteristics that can influence the probability of treatment. The conditional independence assumption requires that the logistic regression equation controls for the set of covariates (X) such that after controlling for these covariates, the potential outcomes are independent of treatment status (T) i.e., $(Y_1, Y_0) \perp T|X)$. There is usually no comprehensive list of the clearly relevant variables that would assure that the matched comparison group will provide an unbiased estimate of treatment. The covariates we control for in calculating the propensity score for the analysis here is informed by past literature on travel behavior and driver response to vehicle automation technology. The list of covariates we control for in the estimation of the propensity score and their potential confounding effect are given in Table 15. Moreover, PEVs with partial automation technology includes not only all the models of Tesla with the Autopilot technology but also the Prius Prime with Toyota Safety Sensing, the PEVs by BMW with BMW Driving Assistance, and other vehicle models by Honda, Kia, Chevrolet, and Ford. As the underlying factors influencing the choice of a Tesla model can differ considerably from the factors driving the choice of a Honda or a Toyota model, we only focus on Tesla owners. This allows us to narrow down the set of covariates to the characteristics of a vehicle owner that may influence the decision to install Autopilot or their VMT or both. The second assumption required for the PSM analysis to hold is the assumption of common support or overlap i.e., for each value of X, there is a positive probability of treatment i.e., $0 < P(T= 1|X) < 1$. If the overlap assumption is violated, one cannot predict or account for the unobserved outcomes for some individuals. When these two assumptions are satisfied, the treatment assignment is said to be random or *strongly ignorable* and an unbiased estimate of the treatment effect can be found [61]. The final assumption of the PSM method is that the outcome and treatment status of each individual are unrelated to the outcome and treatment status of all other individuals (also called the IID assumption).

Table 15. Covariates for the propensity score estimation

Covariates	Potential confounding effect
Lifestyle factor: Likes suburban living	Can affect both choice of automation and VMT
Lifestyle factor: Pro-technology interacted with the respondent age	Can affect the choice of automation
Lifestyle factor: Likes outdoor lifestyle	Can affect both choice of automation and VMT
Lifestyle factor: Unpleasant commute	Can affect the choice of automation
Household income	Can affect the choice of automation and VMT
Residential neighborhood type (Urban/ Rural/Sub-urban)	Can mainly affect VMT
Commute distance	Can mainly affect VMT. May affect choice of automation
Vehicle type (Sedan/SUV)	Can mainly affect VMT
Number of licensed drivers in the household	Can mainly affect VMT
Number of vehicles in the household	Can mainly affect VMT
Whether drivers have access to free charging (e.g., free supercharging)	Can affect the VMT as well as choice of automation
Age of primary driver	Can affect both choice of automation and VMT

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