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PLUG-IN HYBRID & ELECTRIC VEHICLE RESEARCH CENTER

of the Institute of Transportation Studies

A first look at vehicle miles travelled in partially-
automated vehicles

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1 **A first look at vehicle miles travelled in partially-automated vehicles**

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1 ABSTRACT

2 This paper contributes to research investigating the impact of automated and partially automated
3 vehicles on travel behavior. This contribution comes from taking a first look at the impact of
4 partially/semi-automated (SAE Level 2) vehicles on travel behavior and potential correlations
5 with vehicle miles travelled (VMT). The results of this study are taken from a questionnaire
6 survey of 3,001 plug-in electric (PEV) owners in the USA, of which 347 own a partially-
7 automated vehicle (e.g Tesla Model S with Autopilot). This study looks at the VMT of different
8 vehicle types in the survey including plug-in hybrids (PHEVs), battery electric vehicles (BEVs),
9 and semi-automated BEVs. This comparison reveals that semi-automated BEVs have
10 significantly higher VMT compared to other vehicle types. Least squares regression is used to
11 understand VMT in semi-automated BEVs further. This reveals a significant relationship
12 between commute distance, age, household income, house type, and the frequency of autopilot
13 use, and annual VMT. It is possible that the results are showing a self-selection causality as
14 owners of these vehicles already drove more prior to them selecting a semi-automated BEV.
15 Nevertheless, this model indicates that as the frequency of autopilot use increases, so does annual
16 VMT. Due to the potential for two ways causality this study cannot determine whether there is a
17 causal relationship between the use of semi-automated vehicle technology and additional VMT.
18 It is hoped that this first look at the impact of partially-automated BEVs will encourage more
19 research and debate in this area with the aim of improving policy responses to partially and fully
20 automated vehicles.

1 1. INTRODUCTION

2 Automated vehicles are not yet available for consumers to trial or use, with the exception of
3 some small vehicle trials often in closed environments. However, partially automated vehicles
4 (SAE Level 2) are available for consumers to purchase and use. Based on sales data taken from
5 SEC filings at the end of Q2 2018 more 200,000 BEVs with semi-automated driving hardware
6 have been sold globally. These vehicles are Tesla BEVs with “Autopilot” which is a SAE level 2
7 partial automation technology (1). Other original equipment manufactures (OEMs) also have
8 vehicles with similar levels of automation, including those sold by Mercedes-Benz, BMW, and
9 others. In this study we focus on partially automated BEVs (Tesla Model S, X, and 3 with
10 autopilot). Understanding vehicle miles travelled (VMT) may have implications for road
11 networks and may also provide insights to the debate surrounding whether fully automated
12 vehicles may change travel behavior.

13 In this study, we use results from a questionnaire survey of 3,001 plug-in electric vehicle
14 (PEV) owners in the United States. Within this sample are 433 owners of Tesla BEVs of which
15 347 have autopilot hardware and software. The sample is not representative of car buyers or
16 drivers in the USA. This sample was chosen as they are a group of early adopters and therefore
17 may be similar types of consumers as the first ones to adopt automated vehicles, they also have
18 experience of automated driving, and may be more knowledgeable about the automated driving
19 systems. The aim of the study is to take a first look at the potential differences in VMT between
20 adopters of BEVs with autopilot and BEVs without autopilot. To do this, we first explore the
21 VMT of different types of PEVs (plug-in hybrid electric vehicles (PHEVs) and BEVs). Next, we
22 estimate a model that includes all PEV adopters in our survey to understand what variables are
23 correlated VMT for the whole sample. Finally, we estimate a model that investigates what
24 variables are correlated with VMT in partially automated BEVs (Tesla BEVs with autopilot).

25 The outline of this paper is as follows; first we review literature that studies the potential
26 impacts of automated vehicles on travel behavior, then we discuss the methods used, we then
27 present the results of this study, and conclude the study with a discussion, implications for
28 policymakers, and future research needs.

30 2. LITERATURE REVIEW

31 Research into the impacts of automated vehicles on travel behavior can be grouped into two
32 types of study based on the methods used. One method to understand the impact of automated
33 vehicles (AVs) is the use of modeling techniques which use assumptions on how people might
34 use the vehicle to understand changed in travel demand and VMT. Another method is to survey
35 consumers and ask them how they might use AVs and how the vehicles could change their travel
36 patterns. There are no studies currently published that model the impact of partially automated
37 vehicles or present empirical evidence on the use of partially automated vehicles on travel
38 behavior. In their discussion of the potential impacts of automated vehicles Fagnant &
39 Kockelman (2) suggest that AVs could lead to reductions in per mile emissions and but may
40 increase travel demand as the vehicles could increase road capacity and increase the mobility of
41 currently underserved groups. None of the studies outlined below consider the impact of semi-
42 automated vehicles.

2.1. Modelling studies

Perrine et al. (3) used a travel demand model to understand any changes to long distance travel because of driverless vehicles. They found that long distance travel could increase by around 12% due to mode shift from airlines to driverless vehicles. Wadud et al. (4) used a framework to model the potential impacts of AVs on emissions, travel demand, and carbon emissions. They highlight considerable uncertainty in what the impacts of the vehicles will be due to the introduction of complementary technologies and other changes in travel behavior. They found that the vehicles could have a positive or negative impact on VMT and emissions depending on how the vehicles are used. This is also highlighted by Sperling (5) who state that the vehicles could reduce VMT if the vehicles are shared, however single occupant AVs would likely lead to increases in travel. Finally Brown et al. (6) calculate possible emissions increases as a result of automated vehicles. They consider the impacts of eco-driving, platooning, efficient routing, and other potential methods to increase efficiency. They consider faster travel speeds and providing mobility to currently underserved populations as ways in which fuel consumption could increase.

2.2. Survey studies

Most surveys on AVs have focused on consumer acceptance or purchase intentions of the vehicles (7–10); however studies also investigate whether consumers believe their travel patterns will change as a result of vehicle automation, often using stated preference methods. A survey by Zmud investigated (11) consumer acceptance and travel behavior impacts of automated vehicles in Texas. The study found no potential increases in VMT. This was due to most respondents believing their routines, routes, activities, or home location would not change. Half of their respondent though did think their inter-city travel would increase due to reduced stress and fatigue of driving there. A survey of 2588 consumers in the USA found that consumer anticipate using AVs for long distance travel which could impact VMT (12).

3. METHOD

The PH&EV Research Center at the University of California, Davis administered a questionnaire survey to 30,000 consumers in 36 states throughout the United States in March and April 2018. The sample contained 20,000 consumers who were PEV owners and 10,000 ICEV owners who were included as a point of comparison. These survey respondents were sent a letter by mail that outlined the survey topics and provided a link to access the survey in addition to a personal token they could use to access the survey. The survey focused on several topics related to electric vehicles, automated vehicles, and shared vehicles. The sections relevant to this study include:

1. Vehicle Purchase Information (including annual per vehicle VMT)
2. Use patterns of autopilot
3. Household information

Vehicle miles travelled were calculated based on respondents self-reported odometer readings and the period they have owned their vehicle. The measure of VMT in this study in on a vehicle by vehicle basis, it is there total number of miles driven by respondents main vehicle per year. Odometer readings that exceed 50,000 miles per year were excluded from the analysis which left 2,600 completed survey respondents (after also excluding surveys and sections that were completed in too short a time). Use patterns of autopilot are based on owners self-reported

1 use of the vehicle automation technology. Respondents were asked to report how often they use
2 autopilot on a scale going from “Never” to “Every Trip”.

3 4 **3.1. Statistical Analysis**

5 Each pairs student t test is used in this study to determine whether the mean VMTs between
6 adopters of each vehicle type compares. Linear least squares regression is used to understand
7 correlations between annual VMT for Tesla BEVs and socio-demographic variables and self-
8 reported autopilot use. The model includes all Tesla BEVs including those who are not using the
9 partial automation capabilities because it’s not available, not installed, or they have decided not
10 to use it.

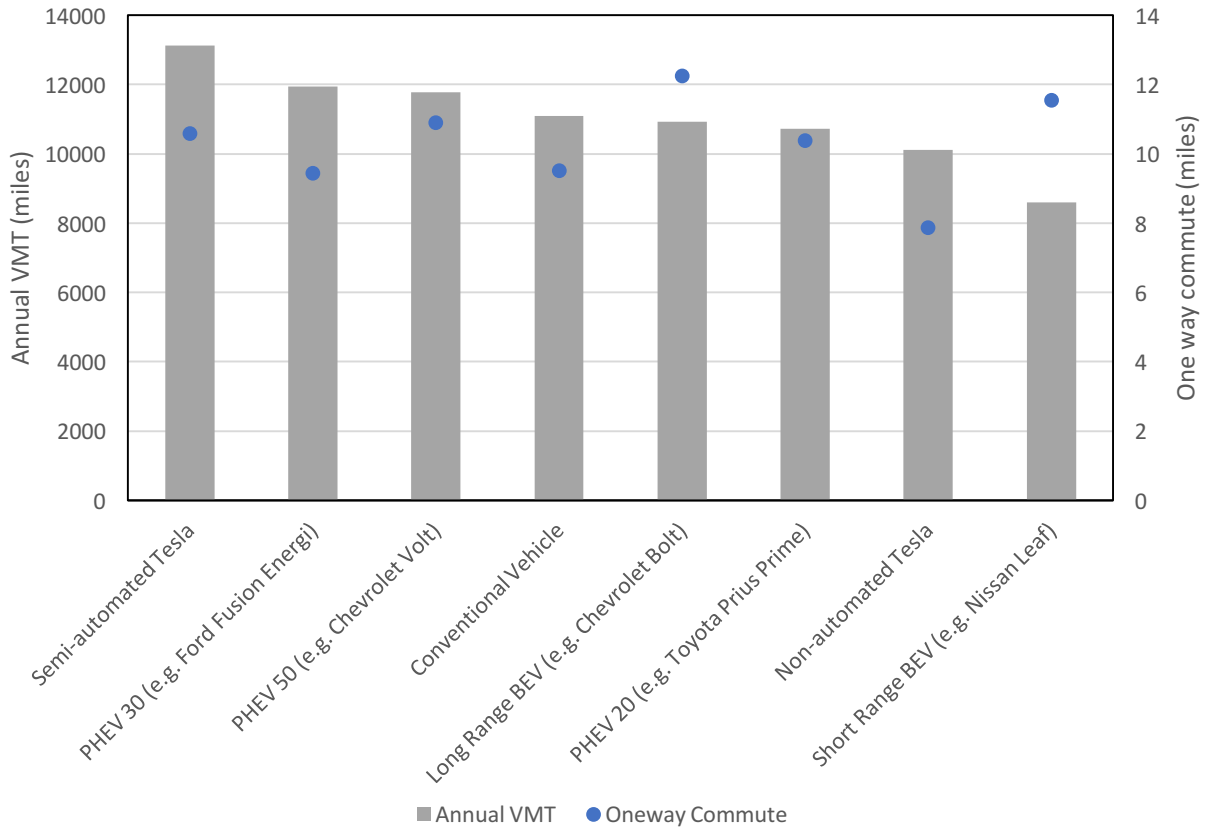
11 12 **4. RESULTS**

13 First, we present the socio-economic profile of respondents to the survey, including the vehicle
14 types they own. Next, we explore the VMT of respondents and finally we model the relationship
15 between socio-demographic and attitudinal variable’s and annual VMT for adopters of partially
16 automated BEVs.

17 18 **4.1. Vehicles in Sample**

19 The vehicles sampled in this study include 426 Tesla BEVs of which 347 have autopilot
20 hardware and software. These vehicles are partially or semi-automated vehicles. Other vehicles
21 sampled in the survey include 200 conventional vehicles, 435 Long Range BEVs (Chevrolet
22 Bolt), 297 PHEVs with 20 miles of range (e.g Toyota Prius Prime), 466 PHEVs with 30 miles of
23 range (e.g Ford Fusion Energi), 382 PHEVs with 50 miles of range (e.g Chevrolet Volt), and 377
24 Short Range BEVs (e.g Nissan Leaf). Figure 1 shows the mean VMT and mean one-way
25 commute distance for each of the household’s primary vehicle. Semi-automated Tesla BEVs
26 have the highest VMT at 13,126 miles per year. The lowest annual VMT is with short range
27 BEVs at 8602 miles per year. The means for VMT and commute distance were compared using
28 each pairs student t-tests. For annual VMT, the mean for Semi-automated Tesla BEVs was
29 significantly higher than all other vehicles at <0.001 , apart from PHEV 30 (0.008) and PHEV 50
30 (0.004). Annual VMT in short range BEVs was also significantly lower at <0.001 against all
31 other vehicle types. There appear to be fewer differences in commute distance were observed.
32 The longest one-way commute distances are in long range BEVs at 12.24 miles each way,
33 though the mean for commuting was only different to non-automated Tesla’s, PHEV 30s, and
34 PHEV 20s. The VMT of semi-automated Tesla BEVs appears to be far higher than other
35 vehicles, despite their being no major difference in their daily commute distances.

36



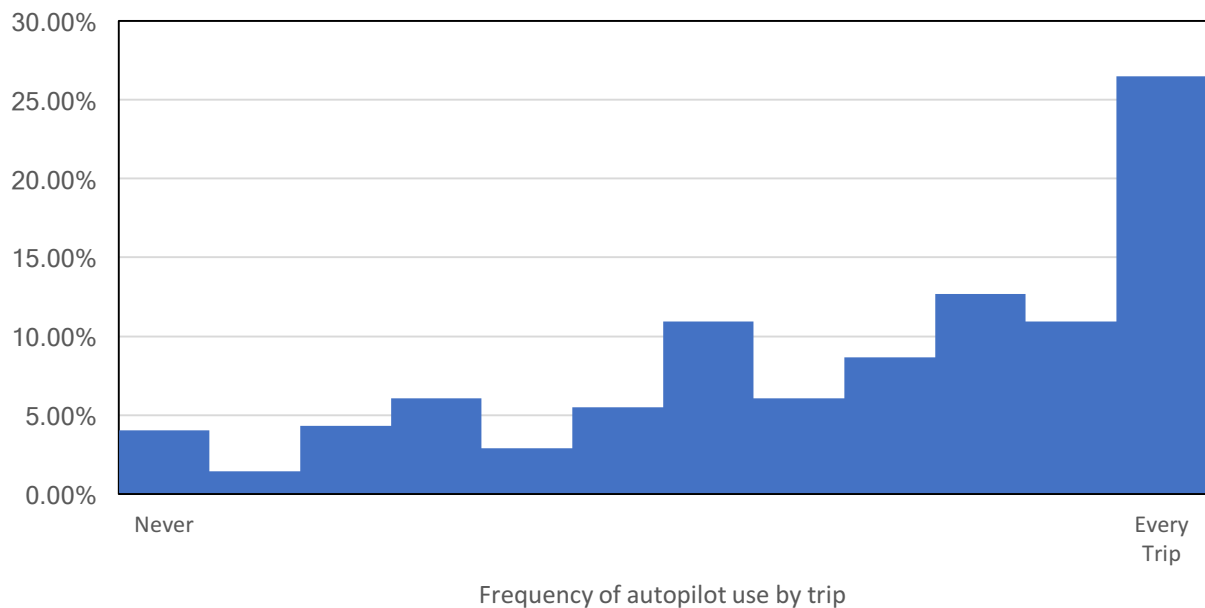
1
 2 **Figure 1: Annual per vehicle VMT and one way commute distance for the vehicles**
 3 **surveyed in this study.**

4 **4.2. Understanding VMT amongst adopters of partially automated BEVs**

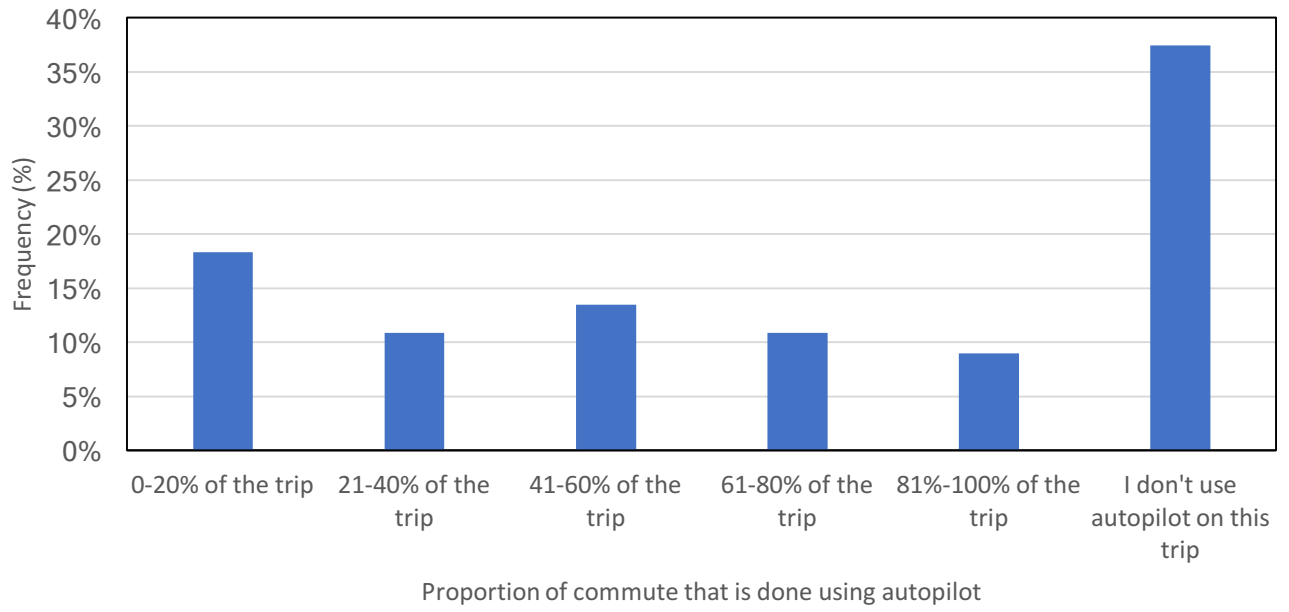
5 In this section, we further investigate annual VMT of Tesla BEVs. First, we present descriptive
 6 statistics and then use a linear regression model to understand the relationship between several
 7 independent variables and annual VMT in Tesla BEVs, including how the use of the semi-
 8 automated driving systems relates to VMT. **Error! Reference source not found.** shows
 9 descriptive statistics for owners of semi-automated Tesla BEVs socio-economic profile and their
 10 household VMT. Chi-square was used to compare the mean VMT for different levels of
 11 education, which showed no trend in Tesla owners level of education. Based on a bivariate
 12 correlation of income and annual VMT there is a negative relationship between household
 13 income and annual VMT for this sample of Tesla owners with autopilot (significant at <0.001).
 14 For all other vehicles in the sample the trend is negative, though not significant. There also
 15 appears to be a positive trend for household vehicles and the number of people in the household,
 16 though this is not significant. Bivariate correlation shows age is negatively correlated with
 17 annual VMT (sig. <0.001), as age increases VMT decreases. Though it should be noted that in
 18 this sample those aged 20-55 have a similar VMT to the US average which is around 15,000
 19 miles per year. However, in this sample those aged 65 and above appear to have a higher VMT at
 20 12,250 miles than the US average of 7,646 for that age group. This suggests the negative trend in
 21 this sample may be less pronounced than for the US on average. VMT between genders is not

1 significantly different in this sample. Finally, there is no clear trend in VMT and the number of
 2 vehicles in the household.

3 To understand how frequently autopilot is used responses were asked to report how often
 4 they use it on a trip by trip basis. The result of this can be seen in Figure 2. The chart shows that
 5 26.5% of those who have autopilot report that they use it on every trip. Only 4% report that they
 6 never use it. The mean likelihood of using autopilot on the scale of 1=Never and 7= Every trip is
 7 5.06, suggesting on average owners of semi-automated BEVs use the automated systems more
 8 often than they do not. Figure 3 shows respondents self reported use of autopilot on their
 9 commute. Survey takers were shown a map which they previously used to indicate their one way
 10 commute and were asked “How much of this trip do you estimate is done using autopilot”.
 11 37.5% of respondents indicated they don’t use autopilot on their commute, indicating 62.5% use
 12 it at some proportion of their commute.
 13



14
 15 **Figure 2: Self-reported frequency of autopilot use on a trip by trip basis (n=347).**



1

2 **Figure 3: Self-reported use of autopilot on respondents' commutes (n=265).**

3

	Level	Number	Mean
HH Vehicles	1	42	13571.4
	2	145	13365.5
	3	89	12550.6
	4	36	11583.3
	5	24	14583.3
HH People	1	38	11473.7
	2	159	12742.1
	3	56	13839.3
	4	61	13836.1
	5	17	14470.6
	6	4	13000
	7	1	13000
Gender	Female	62	12161.3
	Male	274	13277.4
HH Income (\$1,000)	<25	1	23000
	50-100	21	15523.8
	100-150	42	14285.7
	150-200	41	14951.2
	200-250	33	14363.6
	250-300	28	12250
	300-350	21	11095.2
	350-400	14	11714.3
	400-450	14	16285.7
	450-500	10	13000
>500	57	10631.6	
Age	<19	1	18000
	19-29	4	11750
	30-39	44	15386.4
	40-49	56	14500
	50-59	76	12592.1
	60-69	90	12711.1
	70-79	53	11075.5
Highest level of education	Some High School	1	8000
	High School Graduate	45	10244.4
	Some College	208	12576.9
	College Graduate	639	11190.9
	Some Graduate School	172	10593
	Postgraduate degree	1079	10501.4
	I prefer not to answer	16	9312.5

1 **Table 1: VMT for partially automated BEVs by highest level of education, age, number of**
 2 **household people, household income, gender, and number of household vehicles.**

3
 4 Least squares linear regression is used to understand which socio-demographics and the
 5 frequency of using a Tesla BEV as it correlates with VMT. The following attributes are included
 6 in the model: Age, gender, whether they own their home, house type, level of education,

1 household income, number of vehicles in the household, average mpg of these vehicles; one-way
2 commute distance; and the frequency of using autopilot on a Likert scale from Never (1) to
3 Every Trip (7). Household size was excluded due to collinearity with age and the number of
4 vehicles in the household.

5 For this analysis, all Tesla BEVs owners are included in the model. Those without semi-
6 automated driving features are assigned “never” or 1 for their frequency of using autopilot. The
7 first iteration of this model can be seen in Table 2. The model was significant <0.001 and had an
8 adjusted R Square of 0.196. This model found that age, one-way commute distance, income,
9 were significantly correlated with annual VMT. Age and income were negatively correlated. Not
10 surprisingly one-way commute distance was positively correlated with VMT, as was the
11 frequency of autopilot use. After controlling for all of the variables described above frequency of
12 autopilot use shows a positive correlation with VMT. Table 2 also shows the final iteration of
13 this model after removing independent variables that were not significant or not close to being
14 significant. This model is significant at the 0.001 level and had an adjusted R Square of 0.203.
15 This model shows that age, one-way commute distance, house type, household income, and the
16 frequency of autopilot use are all significantly correlated with VMT in Tesla BEVs. Income still
17 returns a negative estimate which means in this sample, controlling for other factors, as income
18 increases VMT decreases. This is an opposite trend that exists among the general population and
19 may be related to the very high incomes of these adopters (\$277,850 on average). With
20 increasing income Tesla owners, may drive less and fly more, for example.

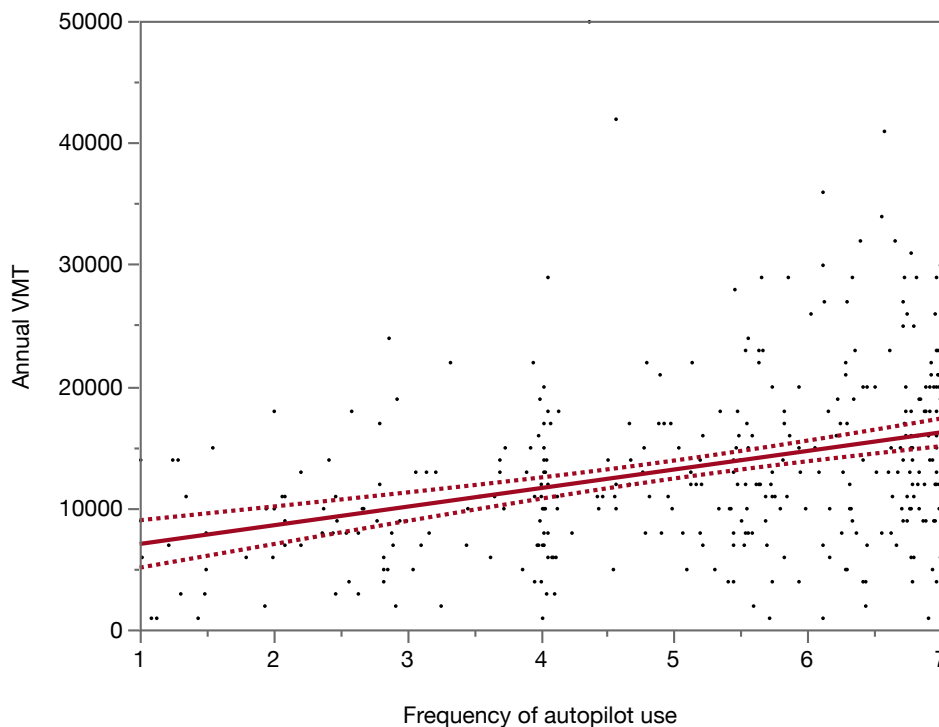
21 This analysis shows that controlling for other factors there is a relationship between how
22 frequently the semi-automated driving system is used and VMT. Figure 4 shows this
23 relationship. This relationship could exist for several reasons. First, drivers with high annual
24 VMT may have planned to purchase a vehicle with partial automation meaning there is a self-
25 selection causality within the data. Second, there may be some causal relationship between use of
26 autopilot and VMT though this study cannot determine if that is the case.
27

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	14509.5	3894.2	3.7	<0.001***
Average household vehicle mpg	-14.4	23.7	-0.6	0.5429
Age	-73.2	26.8	-2.7	0.0066**
Gender	-22.3	446.6	-0.1	0.9601
One way commute distance	85.8	20.4	4.2	<0.001***
House ownership (Own 1, Else 0)	1075.9	2136.9	0.5	0.615
House type (Detached 1, Else 0)	1936.7	1232.4	1.6	0.117
Highest level of education	-1855.3	1215.2	-1.5	0.1278
Income Midpoints	-7.1	2.4	-2.9	0.0035**
Number of vehicles in the household	-163.7	467.8	-0.4	0.7266
Frequency of autopilot use	877.8	168.0	5.2	<0.001**
Prob > F				<0.001**
RSquare Adj				0.196

1

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	12525.7	1976.4	6.3	<0.001***
Age	-76.9	26.2	-2.9	0.0036**
One way commute distance	78.5	19.4	4.1	<0.001
House type (Detached 1, Else 0)	2262.1	1133.5	2.0	0.0467*
Household Income	-7.8	2.3	-3.4	<0.001***
Frequency of autopilot use	916.6	158.9	5.8	<0.001***
Prob > F				<0.001***
RSquare Adj				0.203

2 **Table 2: Least squares regression analysis of VMT in Tesla BEVs (n=337).**



3
4 **Figure 4: Frequency of autopilot use on a scale of 1=Never to 7=Every trip for adopters of**
5 **Tesla BEVs and annual VMT of their Tesla BEV with autopilot (n=337).**

5. CONCLUSION AND DISCUSSION

The results in this study show that owners of semi-automated BEVs have significantly higher VMT than the other types of PEVs included in this sample. In the sample of semi-automated BEV owners, there is a negative relationship between income and age, and VMT. Though there is a negative relationship for age, those 65 years and older still have a higher VMT than the average American in that age group. Least squares regression revealed a correlation between age, income, commute distance, house type, the frequency of autopilot use, and VMT. This suggests that higher use of semi-automated driving systems is related to higher annual VMTs in this sample.

This study aimed to provide an early explorative look on the potential impacts of automated vehicles on VMT. It is hoped that this will encourage more research into the impact of partially automated vehicles, which are on the roads today, and not just fully automated vehicles whose market introduction has not yet begun. The aim of the study was not to understand any causal relationship that may impact VMT in partially automated BEVs, rather the study aimed to provide an early look at VMT in these vehicles.

The results appear to indicate that VMT in partially automated BEVs is significantly higher than in any other group in this sample, and that there is a relationship between use of semi-automated driving and VMT. However, this study cannot determine a causal relationship and the purchase or use of self-driving technology. Self-selection causality could mean those who drive more opted to purchase a BEV with partial automation. In addition, the presence of free superchargers for Tesla BEVs and the fact that the vehicle is a BEV could also be related to drivers higher VMT when compared to other vehicles. However, semi-automated driving systems may increase the comfort of driving, increase safety perceptions, reduce driver fatigue, and increase the potential to multi-task for drivers. These factors could reduce the negative utility driving and increase car owner's willingness to drive, thus increasing their VMT. There is also a correlation between semi-automated usage and commute distance. This may create a secondary effect of drivers selecting land use changes and being willing to undertake longer commutes.

The results in this study may also suggest that automated vehicles could increase VMT. Partially automated vehicles cannot be used as a single occupant vehicles so will not increase travel due to consumer sending their vehicles on errands or allowing them to circle rather than park. However, the vehicles have some similarities due to the reduced fatigue and increased comfort of driving. Therefore, research into semi-automated vehicles may capture some travel behavior changes that result from full vehicle automation.

More research is needed to determine if there is a causal relationship between the partial automation technology in these vehicles and higher VMT. This could include qualitative studies that ask owners of partially automated BEVs whether they perceive their travel behavior to have changed. Studies could also use vehicle trials and place partially automated BEVs in household and investigate travel patterns before and after the vehicle trial. Finally, it may be possible to obtain data from OEMs that includes vehicle VMT prior to the introduction of their automated driving systems. Tesla, for example, sold vehicles with autopilot hardware installed prior to the software. These vehicles were used as non-automated vehicles and then received a software update that made them partially automated vehicles, investigating this trend may reveal causal relationships.

1 5.1.Policy recommendations

2 At present there is a lot of interest in what impact fully automated and self-driving vehicles will
3 have on consumers travel patterns. Policymakers are motivated to understand the potential
4 changes to travel patterns so that any negative consequences can be avoided. These vehicles are
5 several years from their market introduction. Semi-automated vehicles are on the roads today and
6 may already be causing substantial changes to drivers travel patterns. This study highlighted the
7 potential for semi-automated vehicles to increase VMT. Though the results are not conclusive
8 policymakers should consider understanding the potential impacts of semi-automated vehicles.
9 Part of this understanding should come from working with researchers to increase the
10 understanding of what impact semi-automated vehicles will have on VMT.

11

12 5.2.Author contributions

13 The authors confirm contribution to the paper as follows. Study conception and design: Scott
14 Hardman & Gil Tal. Data collection: Scott Hardman, Rosaria Berliner, & Gil Tal. Analysis and
15 interpretation of results: Scott Hardman, Rosaria Berliner, & Gil Tal. Draft manuscript
16 preparation: Scott Hardman. Final manuscript preparation: Scott Hardman, Rosaria Berliner, &
17 Gil Tal.

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