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Battery Electric Vehicles: Travel Characteristics of Early Adopters

Yunwen Feng [1], Jean-Daniel Saphores [2], Hilary Nixon [3,*] and Monica Ramirez Ibarra [2]

1 Institute of Transportation Studies, University of California Irvine, Irvine, CA 92697, USA
2 Department of Civil and Environmental Engineering, Institute of Transportation Studies, University of California Irvine, Irvine, CA 92697, USA; saphores@uci.edu (J.-D.S.); monicr5@uci.edu (M.R.I.)
3 Mineta Transportation Institute, San José State University, San Jose, CA 95192, USA
* Correspondence: hilary.nixon@sjsu.edu; Tel.: +1-408-924-7564

Abstract: Do U.S. households with battery electric vehicles (BEVs) drive less or more than U.S. households with internal combustion engine vehicles (ICEVs)? Answering this question is important to policymakers and transportation planners concerned with reducing vehicle miles traveled and the emissions of greenhouse gases from transportation. So far, this question has not been answered satisfactorily, possibly because of the relatively low number of EVs in the U.S. until recently, but also because of methodological issues. In this paper, we aim to fill this gap by analyzing data from the 2017 National Household Travel Survey (NHTS). We apply propensity score matching (PSM), a quasi-experimental method, to examine the differences in self-reported annual mileage and calculated daily mileage for various trip purposes among households with only BEVs (BEV-only), households with both BEVs and ICEVs (BEV+), and households without BEVs (non-BEV households). Our findings indicate that households with BEVs drive fewer annual miles than non-BEV households, but typically travel no less than they do for daily activities. This apparent discrepancy is likely due to taking fewer longer trips because the public charging infrastructure was still in its infancy in 2017, and its reliability was questionable. As technological progress is helping to overcome current battery limitations, policymakers may consider measures for fostering fast charging technologies while pondering new measures to fund both the charging infrastructure and the road network.

Keywords: battery electric vehicles; household travel; National Household Travel Survey (NHTS) 2017; propensity score matching

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1. Introduction

Do households with battery electric vehicles (BEVs) drive more or less than households with internal combustion engine vehicles (ICEVs)? Microeconomic theory suggests that BEVs will be driven more since the marginal cost of driving is lower for EVs than for ICEVs. Some recent studies find that BEVs are driven *at least as much as* ICEVs [1–4], but others disagree (e.g., see [5,6]), possibly because of range anxiety [7]. However, none of these papers (or related papers we found during our literature review) controlled for self-selection, i.e., variables known to impact the adoption of BEVs such as household characteristics, land use, or the presence of charging station around home and the workplace.

To address this gap, we analyze data from the 2017 National Household Travel Survey (NHTS) to compare various measures of household travel (including vehicle miles traveled (VMT)) of early adopters of battery electric vehicles with those of comparable households using propensity score matching (PSM). We consider both self-reported annual mileage and 2017 NHTS survey day VMT to link any detected differences in mileage to specific travel purposes.

As explained by Angrist and Pischke [8], an ideal research design would use random assignment into treatment (here, access to a BEV) and control groups to attempt to remove biases so differences in VMT between these two groups can be attributed to the treatment (here, BEV use). Since randomized trials are typically infeasible in social science research, the next best alternative is a quasi-experimental approach (such as regression discontinuity, instrumental variables, matching and propensity score, or comparative interrupted time series; see [9]) to assess causal effects when analyzing non-experimental data. Given our dataset, we relied here on propensity score matching [10] to tease out the impact on household VMT of BEV access after controlling for self-selection. In this context, self-selection means that the characteristics of households with access to at least one BEV and land use around their residence or workplace likely differ from those with only ICEVs, so they are likely to travel differently because of concerns about charging time and charging infrastructure limitations. Ignoring self-selection would bias a comparison and lead to misleading conclusions. In the rest of this paper, households with only BEVs are labeled BEV-only, and those with BEVs and ICEVs are called BEV+. We compare them separately with non-BEV households.

When data were collected for the NHTS 2017, just over half of all registered BEVs in the U.S. were in California [11]. Because the 2017 NHTS includes oversampled add-on jurisdictions, BEV households are concentrated in a handful of states. To control for state differences in gas prices and EV incentives (see [12] for an analysis of state EV incentives), our models include state-specific constants, and we analyze the four U.S. states (California, Georgia, New York, and Texas) with the largest number of households with BEVs.

Understanding how much households drive electric vehicles is important for at least two reasons. The first one is the potential impact of vehicle miles traveled (VMT) on the transportation infrastructure and energy systems (particularly the energy grid). With current battery technologies, BEVs are typically heavier than similar ICEVs, so they damage roads more but do not contribute directly to funding their repair through fuel taxes. At the end of 2023, 24 states had imposed a higher annual vehicle registration fee for electric vehicles and some hybrid vehicles than for ICEVs to help offset forgone gas tax revenue. These fees ranged from USD 50 in Hawaii and South Dakota to USD 200 in Ohio, West Virginia, and Wyoming.

The second reason is the impact of BEV VMT on the electricity grid, and emissions of greenhouse gases. The charging infrastructure needed to support BEV adoption is still insufficient, and new investments must be carefully planned to ensure that they meet the needs of EV users without hindering our efforts to reach greenhouse gas (GHG) reduction goals. Kapustin and Grushevenko [13], for example, argued that demand peaks for electricity could pose a challenge for the grid and that a "business-as-usual" solution may require increasing fossil fuel consumption to produce electricity. Policies to address this problem require understanding potential changes to BEV VMT. Six states (Georgia, Iowa, Kentucky, Montana, Oklahoma, and Utah) already tax the electricity dispensed at EV charging stations [14].

To curb energy demand and road congestion, states are increasingly considering policies to reduce VMT. California's Senate Bill 375, for example, requires metropolitan planning organizations to develop a sustainable communities strategy (SCS) within each long-range transportation plan [15]. Each SCS must include plans to reduce VMT to meet climate goals. In 2021, the Washington State legislature directed its Department of Transportation (DoT) to develop guidelines to reduce per capita VMT [16]. In 2020, the Minnesota DoT set a statewide goal of reducing VMT by 20% by 2050 [17]. Understanding how the transition to EVs might affect progress toward these goals is therefore necessary as the emission benefit of BEVs depends on how many gasoline miles are replaced.

In Section 2, we review selected papers on BEV ownership and travel. We then discuss our data in Section 3. Section 4 details our methodology, and Section 5 presents our findings. Finally, in Section 6, we summarize our contributions, discuss some policy recommendations, outline limitations of our work, and make suggestions for future research.

2. Literature Review

A small but growing body of research has explored the travel behavior of households with BEVs. This section reviews studies that examine the mobility patterns of EV drivers.

In addition, we briefly summarize key findings from the literature on the characteristics that influence EV adoption, which informed our modeling approach.

2.1. How Are EVs Used?

Although U.S. electric vehicle sales have soared over the last decade, they still represent only a small percentage of total vehicle sales, reaching 5.8% of all vehicles sold in 2022, up from 3.2% in 2021, according to figures released by the market research firm Motor Intelligence. When the 2017 NHTS was conducted, only 0.1% of the U.S. passenger vehicle fleet was electric [18]. Research analyzing travel behavior is still somewhat limited. A recurring theme of this literature is the impact of charging constraints on travel—how frequently EV drivers charge their vehicle. The time/distance between charging events and the infrastructure needs to support a transition to electric vehicles [19–23]. This is not a focus of our study, so we do not review this literature. Our interest is primarily in comparing the number of trips, the total distance traveled, and the total travel time between households with BEVs and those without EVs, as well as trip purpose. Surprisingly, we did not identify any existing study that used a quasi-experimental design approach to control for the characteristics of BEV owners (or those of their household) when exploring their travel patterns or when comparing them with those of non-BEV households.

Several studies analyzed 2017 NHTS data to better understand EV travel behavior in the U.S. Davis [5] looked broadly at how much EVs are driven in the U.S. and in California compared to other vehicle types, but did not consider specific household characteristics other than the number of vehicles per household. Li et al. [6] compared the usage of alternative fuel vehicles, including BEVs, to ICEVs for trip distance and trip duration. They found that both mean trip distance and mean trip duration for BEVs is less than for ICEVs, while their 85th percentiles were similar for both vehicle types. On the other hand, when [2] controlled for vehicle characteristics, specifically EV range, the difference in annual miles driven between BEVs and ICEVs disappeared. At the time of the 2017 NHTS data collection, there were only a few long-range EVs on the market. However, that has changed with an increasing number of EVs capable of driving 300+ miles on a single charge. In their 2020 study for the California Air Resources Board, Tal et al. [21] noted that the 2017 NHTS data consist primarily of early adopters of first-generation BEVs and might not accurately reflect changes in use as EV technology advances.

Tal et al. [24] studied plug-in electric vehicles (both BEVs and plug-in hybrid vehicles (PHEVs)) in California, focusing primarily on charging behavior. They considered total daily miles driven, number of trips, and trip distance, by weekday and weekend. As with [5], they did not examine trip purpose or incorporate socioeconomic characteristics into their analysis. Jia and Chen [3] examined annual miles driven by California households for three zero-emission vehicle (ZEV) types (BEVs, PHEVs, and fuel cell electric vehicles (FCEVs)) compared to ICEVs. On average, ZEVs have higher annual mileage than ICEVs. They did not, however, explore trip purposes to understand how ZEVs are used compared to ICEVs. Chakraborty et al. [1] analyzed a unique dataset from repeated surveys of BEV owners in California and found that these vehicles are driven a similar number of annual miles as ICEVs.

Since many new vehicle models now include comprehensive onboard telematics—which provide a wealth of information such as location, charging information, speed, and acceleration—several studies have leveraged this data source to explore EV usage. Yang et al. [25] conducted a geospatial analysis of EV drivers in Beijing, China. Thanks to the fine-grained GPS data available, they were able to examine travel destinations based on known "points of interest," although specific trip purpose (i.e., work, shopping, etc.) was not available. They reported that weekday and weekend travel do not vary significantly, even when considering commercial points of interest, which they hypothesized would be associated with commuting. Most EV drivers traveled to repeated destinations within a small geographical area over the month-long period of their data collection. Jensen et al. [26] analyzed the travel behavior of Danish households who own both BEVs and

ICEVs to compare route choices. BEVs, in general, were used for shorter trips, although a key limitation was the reduced range of the electric vehicles at the time compared to ICEVs. Other studies analyzed telematics data to explore travel behavior [27–29], but their primary objective was to better understand how charging requirements may affect travel.

To circumvent the lack of driving data due to the small number of EVs in use in the U.S., several studies simulated their use based on data from ICEVs or relied on hypothetical scenarios (see [30], and references therein). For example, Langbroek et al. [31] built a stated adaptation experiment to understand how drivers in Sweden would change their travel patterns due to EV range limitations. Their findings indicate that those who thought that the experiment's range limitation was not constraining traveled more and relied less on alternatives such as public transit. However, some participants did limit their travel, choosing to cancel non-essential trips such as shopping or visiting relatives. Jensen and Mabit [30] looked at actual trip data from a large-scale EV trial in Denmark to examine different travel patterns for EVs compared to conventional vehicles in multivehicle households, but they neither examined trip purpose nor controlled for household characteristics.

2.2. Who Drives EVs?

A larger body of literature explored what influences EV adoption, although many of these studies relied on stated preference and survey methods to predict potential buyers (e.g., see [32–37]). A few papers, however, analyzed actual user data (e.g., see [38–40]) to characterize EV owners. While the focus of our study is not to predict who drives EVs, this body of research did provide some helpful insights.

Examining this literature helped identify key explanatory variables for our logistic regression models, which form the building block for the propensity score matching technique we relied on for our analysis. Two comprehensive literature reviews [19,41] and a detailed meta-analysis [42] on EV adoption proved extremely helpful, so we focus on these studies here. According to these references, three primary groups of variables can be used to explain EV ownership: (1) external factors such as vehicle characteristics (e.g., range, charging time, price, etc.), infrastructure (i.e., charging availability), and policy (e.g., rebates, tax incentives, access to high-occupancy/express lanes, etc.); (2) internal attributes including socioeconomic and demographic variables, psychological factors, current travel behavior (e.g., annual miles driven or commuting patterns); and (3) spatial variables such as built environment and land use characteristics. Building on these results, we selected relevant variables for implementing propensity score matching.

3. Data and Variable Selection

This section summarizes how we prepared our dataset. The 2017 NHTS provides a comprehensive picture of travel by U.S. residents in all 50 states and the District of Columbia. It includes data on trips made by all modes and for all purposes. Its national core was designed using an address-based sample survey from the U.S. Postal Service's computerized delivery sequence file to give each household an equal probability of selection; it was supplemented by samples from 13 add-on areas comprising a mixture of states and MPOs. Travel information for the 2017 NHTS was collected between April 2016 and May 2017 [43]. It is important to recognize the limitations of the NHTS data as they underrepresent some racial and ethnic groups, particularly Black and Latino households [44]. This matters because non-Hispanic Whites have a greater share of automobile trips than other racial and ethnic groups and a lower share of non-automobile trips such as transit, biking or walking [45]. Our focus here is on household vehicle travel behavior and the research method used matches households across a wide range of characteristics, so potential impacts are minimized. However, it is important to consider our results in light of the limitations of the dataset we analyzed.

The 2017 NHTS public dataset is organized in four files (households, persons, trips, and vehicles), which contain data from 129,696 households corresponding to 264,234 individuals who undertook 923,572 trips in 256,115 vehicles on their assigned survey day (The public version of the 2017 NHTS data can be downloaded from https://nhts.ornl.gov/downloads (accessed on 14 May 2024)). We extracted and combined data from each of those files and added variables about the availability of public EV charging infrastructure after requesting location data for the states with the most BEVs, as explained below.

3.1. Vehicle and Charging Station Data

In the vehicle file, we first focused on vehicles whose fuel was reported to be electricity. After checking vehicle make, model year, and type (i.e., car, van, SUV, pickup truck, other truck, RV, motorcycle/motorbike, or something else), we kept only BE cars and SUVs available for sale in the U.S. through model year 2017 based on information from the U.S. Department of Energy [18] (see Table 1). We then checked that all Tesla vehicles and specific electric vehicles (the Nissan Leaf) had been flagged as BEVs.

Table 1. BEV make and model.

Make (Model)	U.S. Number	CA Number
Chevrolet (Bolt, Spark)	17	16
Fiat (500e)	27	27
Ford (Focus)	6	5
Honda (Clarity, Fit)	3	2
Kia (Soul)	5	3
Nissan/Datsun (Leaf)	191	94
Smart (Fortwo)	10	6
Tesla (Model X, Model S, Model 3, Roadster)	128	80
Toyota (RAV4)	5	4
Volkswagen (e-Golf)	14	13
Total	406	250

After this step, we were left with 406 clearly identified BEVs nationwide. Four states (the number of BEVs is in parenthesis)—California (250), Georgia (39), New York (19), and Texas (44)—account for 87% of the BEVs in our dataset. One component of our methodology involves characterizing households with BEVs. In addition to socioeconomic variables, land use, the price of gasoline, and the presence of charging stations, incentives to purchase BEVs (such as tax rebates or access to HOV lanes) are relevant [12,46]. To capture state-specific incentives, we introduced state binary variables. Since most states had only at most a few BEVs, we restricted our analysis to California (CA), Georgia (GA), New York (NY), and Texas (TX).

After extensive checks, we collapsed our vehicle dataset by household and added two variables to characterize the availability of public charging infrastructure in 2016: the number of charging stations per square mile and the number of charging stations per 100,000 persons in a household's CBSA (core-based statistical area). They were obtained from the California Energy Commission based on data gathered from the U.S. Department of Energy's Alternative Fuels Data Center. Figure 1 shows the distribution of BEV households in California, Texas, and Georgia, along with the density of charging stations per 10,000 persons. (We used density per 100,000 persons in our models to adjust the magnitude of the corresponding coefficient). Our map does not include New York because the location of NY respondents in the 2017 NHTS is not available to researchers.

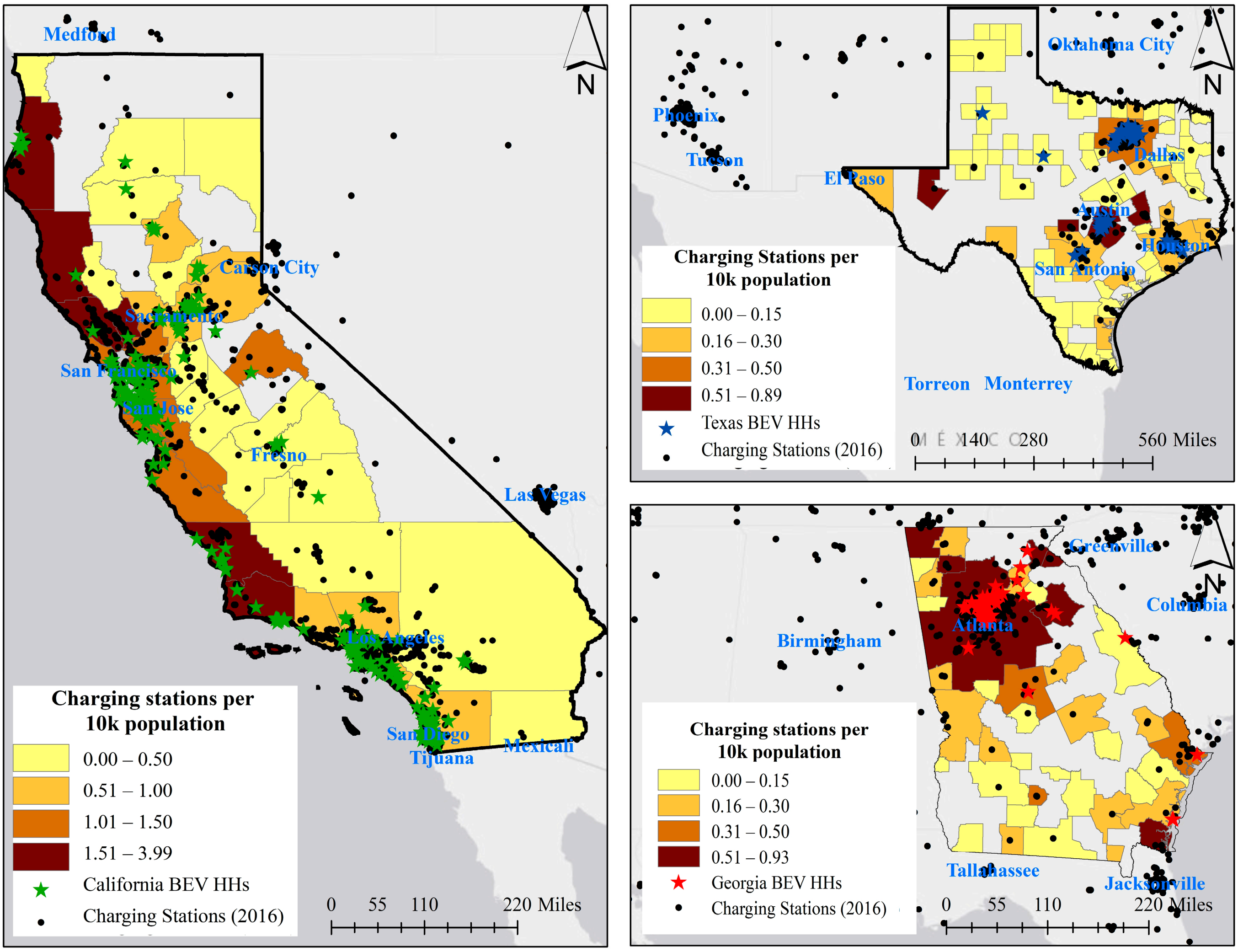

Figure 1. Location of BEV households and charging stations in California, Texas, and Georgia.

After this step, our sample had 123,447 households with at least one vehicle:

- A total of 33 households whose only vehicles are BEVs ("BEV only households");
- A total of 361 households who have at least one BEV and one ICEV ("BEV+ households");
- A total of 123,053 households that only have non-BE vehicles ("Non-BEV households").

Since California has the largest number of BEVs in the 2017 NHTS and we gained access to household locations, we created a California-specific dataset, with variables indicating the availability of public EV charging stations within 1 and 2 miles of each household's residence. After this step, our California dataset had 24,929 households with at least one vehicle, including the following:

- A total of 23 households whose only vehicles are BEVs ("BEV only households");
- A total of 220 households who have at least one BEV and one ICEV ("BEV+ households");
- A total of 24,686 households who only have non-BE vehicles ("Non-BEV households").

3.2. Individual and Household Data

Based on our literature review, the variables we selected for our analysis to model whether a household has BEVs include age, household size and composition, racial and ethnic makeup, income, education, and homeownership. We also considered the number of household drivers and vehicles, and some land use variables.

Some EV ownership studies show that age matters [32,36,38]. Since our analysis is at the household level, we created variables that keep track of adult members from different generations (counts of adult members from different generations led to multicollinearity issues with household size). To define generations, we relied on definitions from the Pew Research Center [47]: Silent Generation (born before 1945), Baby Boomers (born between 1946 and 1964), Generation X (born between 1965 and 1980), Generation Y (also known as Millennials, born between 1981 and 1996), and Generation Z (born after 1996 but before 2000 since we analyze household members 18 and over).

Household size and composition may affect vehicle ownership and use (e.g., see [19,42], and references therein). Household composition reflects the presence of adults, retirees, and children within the household. For simplicity, we recombined the NHTS life cycle variables as follows: (1) one adult, no children; (2) two or more adults without children; (3) one adult with at least one child; (4) two or more adults with at least one child; (5) one retiree without children; and (6) two or more retirees without children.

Race and Hispanic status may also impact BEV ownership and travel behavior [48,49]. For the former, if all members of a household were of the same race, we assigned that race to the household; otherwise, the household was deemed multiracial. For Hispanic status, we simply relied on the status of the household head in the NHTS data, as in [48,50].

Income is known to be an important predictor of EV ownership and matters for travel [32,38,40]. In the 2017 NHTS, household annual income is divided into 11 categories. For simplicity, we aggregated them into five categories: (1) USD 24,999 or less; (2) USD 25,000 to USD 49,999; (3) USD 50,000 to USD 74,999; (4) USD 75,000 to USD 124,999; and (5) USD 125,000 or more.

Education attainment is often influential in EV studies [32,36,38,40]. We captured the highest education level within the household (i.e., the maximum educational attainment of all adults) using the following categories: (1) high school graduate/GED or less; (2) some college or associate degree; (3) bachelor's degree; (4) graduate or professional degree.

Since recharging at home is valued by many potential EV owners [51], and owning a home enables installing an EV charger, we used in our models binary variables that indicate if a household owns (vs. rents) their home. We also included the number of drivers and vehicles in the household.

To reflect land use, we followed the literature [49,52,53] given the variables available in the 2017 NHTS and considered population and employment density in the census tract of the household's home location, but we had to drop employment density because of multicollinearity. As mentioned above, we created state binary variables to account for differences in gasoline prices and state incentives for BEVs.

After excluding observations with missing data (e.g., age, income, race), collapsing individual variables to the household level, and merging them with household variables, our sample after this step had 117,932 households, including 23,816 in California.

3.3. Travel Data

In the 2017 NHTS dataset, three options are available to analyze the number of miles driven by a household. First, we could rely on the reported annual mileage for all household vehicles (variable "ANNMILES"). Unfortunately, over a quarter of the vehicles in the 2017 NHTS dataset have missing odometer data, and the quality of some odometer readings was questioned by the NHTS team [54].

Second, we could analyze the estimate of annual miles driven for each NHTS vehicle that was generated by the Oak Ridge National Laboratory (reported in the variable BESTMILE). However, the methodology used for these calculations is essentially unchanged from the 2001 NHTS, and it makes no special considerations for electric vehicles, so we did not use that approach.

Third, we could analyze vehicle mileage during the survey days designated by the NHTS, during which respondents keep a log of all their travel. While in 2009, respondents reported their VMT for each trip, in 2017, they provided the origin and the destination of each of their trips, and their VMT was calculated using Google APIs. Here, we used the first and third approaches.

For the latter, we removed trips with missing data, duplicate vehicle trips (where passengers and driver are from the same household), and trips taken by modes other than household vehicles. We also dropped observations with inaccurate trip durations (e.g., zero or negative travel time), those longer than 1000 miles on the survey day, and trips with excessive speed (>75 mph for household vehicles). We then aggregated trip purpose into nine categories: (1) home; (2) work; (3) school/daycare/religious activities; (4) medical/dental services; (5) shopping/errands; (6) social/recreational; (7) transport someone; (8) buy meals; and (9) something else. We excluded "home" and "something else". Trip records were then collapsed by household.

3.4. Final Dataset

Our final dataset has information about 67,245 households, of which 30 are "BEV only" and 300 are "BEV+" households (see Table 2). The California subset has 23,295 households. It includes 23 "BEV only" and 212 "BEV+" households, which represent 76.7% of the "BEV only" and 70.7% of the "BEV+" households in our four-state dataset.

Table 2. BEV+ and BEV-only households, by state.

State	Number of BEV-Only Households	Number of BEV+ Households
California	23	212
Georgia	2	35
New York	1	17
Texas	4	36
All other states (excluded from the final dataset)	*3*	*49*
Total	33	349

Table 3 presents summary statistics for the variables used in our models for these three groups of households. The most obvious difference between BEV-only households and both BEV+ and non-BEV households is that BEV-only households tend to be smaller, with fewer vehicles, and they are more likely to have more drivers than vehicles. BEV households also tend to be located in areas with a higher population density. Compared to non-BEV households, BEV-only and BEV+ households usually have a higher income and more education. Moreover, BEV-only and BEV+ households are more ethnically and racially diverse than non-BEV households, although there are no African American/Black households with BEVs in our sample. The greater racial diversity of BEV households is driven by the high percentage of California households in our four-state sample. It is important to note that the sample size of BEV-only households is quite small, so generalizations are risky.

It is also informative to peruse summary statistics, grouped by BEV ownership, for the number of trips, trip duration, and trip length, as shown in Table 4. As our analysis shows, reaching conclusions simply based on these aggregate statistics can be misleading.

From Table 4, BEV-only households in the four-state sample took on average 1.5 fewer vehicle trips per weekday than non-BEV households and 3.5 fewer vehicle trips per weekday than BEV+ households. Moreover, BEV-only households took shorter trips than BEV+ (24.5 mi per day) and non-BEV households (10.2 mi per day). As a result, BEV-only households drove 27.7 fewer minutes on weekdays than non-BEV households and 64.9 fewer minutes than BEV+ households. On weekends, BEV-only households took slightly fewer trips than BEV+ households (3.9 vs. 4.7) and the same number of trips on average as non-BEV households. They drove less far and did not spend as much time traveling as the other two groups of households. Similar patterns hold for the California sample.

Table 3. Summary statistics for BEV-only, BEV+, and non-BEV households.

	BEV-Only		BEV+		Non-BEV	
	4 States	CA	4 States	CA	4 States	CA
Household generations						
Silent Generation	0.133	0.130	0.080	0.080	0.213	0.231
Baby Boomer	0.333	0.304	0.490	0.505	0.510	0.512
Generation X	0.467	0.435	0.503	0.481	0.291	0.286
Generation Y	0.133	0.174	0.223	0.231	0.237	0.232
Generation Z	0.000	0.000	0.087	0.090	0.041	0.040
Household structure						
1 adult, no children	0.400	0.435	0.053	0.061	0.172	0.165
1 adult, children	0.133	0.087	0.300	0.302	0.222	0.217
2+ adults, no children	0.067	0.043	0.183	0.184	0.245	0.259
2+ adults, children	0.133	0.174	0.430	0.420	0.199	0.188
1 retiree, no children	0.200	0.261	0.017	0.019	0.127	0.139
2+ retirees, no children	0.067	0.043	0.183	0.184	0.245	0.259
Household size (range: 1–12)	1.700	1.696	2.850	2.802	2.188	2.168
Number of household workers (range: 0–7)	1.033	0.957	1.523	1.547	1.041	1.012
Household race						
White	0.667	0.609	0.790	0.741	0.825	0.802
African American/Black	0.000	0.000	0.017	0.014	0.065	0.028
Asian	0.200	0.261	0.150	0.184	0.051	0.083
Other	0.133	0.130	0.043	0.061	0.059	0.087
Hispanic	0.133	0.087	0.043	0.052	0.094	0.105
Household annual income						
USD 0 to USD 24,999	0.100	0.130	0.023	0.009	0.156	0.146
USD 25,000 to USD 49,999	0.100	0.130	0.033	0.033	0.213	0.199
USD 50,000 to USD 74,999	0.033	0.043	0.060	0.057	0.179	0.170
USD 75,000 to USD 124,999	0.167	0.043	0.240	0.222	0.250	0.255
USD 125,000 and above	0.600	0.652	0.643	0.679	0.202	0.230
Household education						
Less than a BS/BA	0.300	0.304	0.067	0.071	0.396	0.376
Bachelor's degree (BS/BA)	0.167	0.217	0.237	0.236	0.273	0.278
Graduate or professional	0.533	0.478	0.697	0.693	0.331	0.345
Homeownership	0.800	0.783	0.910	0.910	0.765	0.726
Number of household drivers (range: 1–9)	1.267	1.261	2.187	2.175	1.748	1.740
Number of household vehicles (1–12)	1.200	1.174	2.797	2.844	2.037	2.086
Population density (#/mi^2):						
0–99	0.067	0.043	0.050	0.057	0.125	0.109
100–499	0.067	0.087	0.107	0.104	0.149	0.098
500–999	0.033	0.043	0.060	0.042	0.077	0.056
1000–1999	0.033	0.043	0.130	0.080	0.122	0.093
2000–3999	0.133	0.087	0.213	0.175	0.194	0.164
4000–9999	0.500	0.478	0.357	0.425	0.261	0.350
10,000–24,999	0.100	0.130	0.077	0.108	0.058	0.112
≥25,000	0.067	0.087	0.007	0.009	0.013	0.018
Household lives in CA	0.767	1.000	0.707	1.000	0.345	1.000
Household lives in GA	0.067	0.000	0.117	0.000	0.112	0.000
Household lives in NY	0.033	0.000	0.057	0.000	0.216	0.000
Household lives in TX	0.133	0.000	0.120	0.000	0.327	0.000
Charging stations						
Number per 100 K persons (range: 2.65 to 17.72)	10.581	- -	10.552	- -	6.562	- -
Public, within 1 mi of residence (range: 0–82)	- -	4.739	- -	1.849	- -	1.520
N	30	23	300	212	66,915	23,060

1. All variables are binary, except for household size; the number of household workers, drivers, and vehicles; and the two charging station variables. 2. Numbers in the table are mean values. 3. "- -" indicates that a variable is not available. 4. BEV-only households have one or more battery electric vehicles and no internal combustion engine vehicles (ICEVs). BEV+ households have at least one of each. Non-BEV households only have ICEVs.

Table 4. Trip summary statistics for BEV-only, BEV+, and non-BEV households.

		4 States: CA, GA, NY, TX				CA Only			
		Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
	Weekdays								
BEV-only N_4 = 23 N_{CA} = 16	Number of trips/day	3.6	2.7	0.0	11.0	2.9	2.0	0.0	6.0
	Travel time (min)	73.6	65.1	0.0	281.0	63.8	49.0	0.0	156.0
	Trip distance (mi)	33.2	34.0	0.0	117.2	30.1	31.8	0.0	97.9
BEV+ N_4 = 218 N_{CA} = 156	Number of trips/day	7.1	4.0	0.0	20.0	7.4	4.01	0.0	20.0
	Time (min)	138.5	92.5	0.0	575.0	143.0	95.3	0.0	575.0
	Trip distance (mi)	57.7	47.9	0.0	269.9	60.5	51.2	0.0	269.9
Non-BEV N_4 = 51,645 N_{CA} = 16,496	Number of trips/day	5.1	3.8	0.0	37.0	4.9	3.8	0.0	35.0
	Travel time (min)	101.3	95.4	0.0	1863.0	98.01	96.8	0.0	1327.0
	Trip distance (mi)	43.4	56.3	0.0	1240	41.1	55.8	0.0	898
	Weekends								
BEV-only N_4 = 7 N_{CA} = 7	Number of trips/day	3.9	2.9	0.0	8	3.9	2.9	0.0	8.0
	Travel time (min)	49.7	54.8	0.0	159	49.7	54.8	0.0	159.0
	Trip distance (mi)	19.5	25.5	0.0	72	19.5	25.5	0.0	71.9
BEV+ N_4 = 82 N_{CA} =56	Number of trips/day	4.7	3.1	0.0	14	4.2	2.9	0.0	12.0
	Time (min)	92.7	84.3	0.0	540	88.1	94.3	0.0	540.0
	Trip distance (mi)	44.01	61.1	0.0	470	44.6	71.6	0.0	469.7
Non-BEV N_4 = 15,270 N_{CA} = 6564	Number of trips/day	3.9	3.2	0.0	27	3.7	3.2	0.0	27.0
	Travel time (min)	77.8	88.6	0.0	1200	75.9	88.3	0.0	1093.0
	Trip distance (mi)	36.0	57.3	0.0	841	34.8	56.1	0.0	651.7

N_4 is the sample size for the four-state dataset (CA, GA, NY, and GA), and N_{CA} is the sample size for the CA subset.

4. Methods

As explained above, we considered three groups of households: BEV-only (households that only own BEVs), BEV+ (households with multiple vehicles of which at least one is a BEV, and at least one is a non-BEV), and non-BEV (households that do not own a BEV but own at least one vehicle).

To control for self-selection bias in analyzing the impact of BEVs on household travel, we used propensity score matching (PSM) [10,55]. With PSM, a group of observations with a treatment (here, the ownership of a BEV) from an observational (nonrandomized) dataset is matched with a group of observations without the treatment based on their probability of being in the treatment group on the condition of observed treatment variables, so the combined dataset has the key characteristics of a randomized controlled trial, and the impact of the treatment can be calculated without bias.

Following [55], let $y_{1,\mathrm{i}}$ denote a measure of travel (e.g., number of trips, trip duration, or trip distance) of household "*i*" if that household participated in the 2017 NHTS and had a BEV. Conversely, let $y_{0,i}$ denote the same outcome variable if that household did not have a BEV. To quantify the causal effect of the treatment (access to a BEV) on household travel, we would like to calculate the difference $y_{1,i} - y_{0,i}$, but we observe only $y_{1,i}$ or $y_{0,i}$ (never both), so we conceptualize this as a missing data problem and view $y_{k,i}$ (k∈{0,1}) as the outcome from random variable $Y_{k,i}$. We can then estimate the impact of the treatment by comparing its average impact between two groups: a treatment group, which has BEVs, and a reference group, which does not. To track if household "$_I$" belongs to either group, we use the binary variable B_i, which equals 1 if household "$_I$" was assigned to the treatment group and 0 otherwise (i.e., if it belongs to the control group). The impact of a measure of travel from BEVs can then be written as follows:

$$\Delta\mu = E[Y_{1,i}|B_i = 1] - E[Y_{0,i}|B_i = 0] \quad (1)$$

Let us now decompose $\Delta\mu$ as follows:

$$\Delta\mu = (E[Y_{1,i}|B_i = 1] - E[Y_{0,i}|B_i = 1]) + (E[Y_{0,i}|B_i = 1] - E[Y_{0,i}|B_i = 0]) \quad (2)$$

Terms in the first set of parentheses on the right side of Equation (2) calculate the average causal effect of a BEV on the dependent variable for households observed in the treatment group; it is the average treatment effect on the treated (ATET). Terms in the second set of parentheses on the right side of Equation (2) represent the self-selection bias, which is the difference between the expected travel of households in the control and travel groups, both without the treatment.

If there is no self-selection bias, $\Delta\mu$ is equal to the ATET. However, in practice, there may be self-selection bias in observational data because households that own a BEV may have different socioeconomic and demographic characteristics from households that do not, or they could reside where land use and charging infrastructure differ.

To reduce self-selection bias, the PSM algorithm matches each household in the control group with one or more households in the treatment group based on the propensity score $e_i(\boldsymbol{X}_i) = Pr(B_i = 1|\boldsymbol{X}_i)$, which represents the probability (estimated via a logit model) that household i has one or more BEVs conditional on the control variables $\boldsymbol{X}_i$ (which include income, education, or household structure; see Table 5). This approach hinges on the proof that matching based on the probability of treatment conditional on all relevant observed covariates $\boldsymbol{X}_i$ is sufficient for obtaining an unbiased estimate of a treatment on an outcome variable [55].

If the matching is comprehensive, the outcome variables become orthogonal to membership in the treatment and control groups conditional on covariates, the bias shrinks to zero, and

$$\Delta\mu = E[Y_{1,i}|\boldsymbol{X}_i] - E[Y_{0,i}|\boldsymbol{X}_i] = E[Y_{1,i} - Y_{0,i}|\boldsymbol{X}_i] \quad (3)$$

As noted in [10], however, PSM can only remove the bias arising from observed covariates $\boldsymbol{X}_i$, but not from unobserved variables such as attitudes, so we cannot exclude the risk of residual omitted variable bias. Moreover, PSM works better (i.e., it removes more of the bias) in larger samples, and in studies where the treated and control groups are from the same social context. In addition, covariates related to the treatment are handled differently if they are not related to the outcome compared to those also related to the outcome [10].

For a PSM model to produce unbiased results, the balancing condition must be verified. This condition says that the distribution of the control variables in the treatment and control groups must be statistically equal. To check this condition, we followed Rubin [56]; we calculated the standardized mean difference between the treatment and control samples, the mean bias, and the ratios of variances for each control variable and each model, and classified the adequacy of our matches as "good", "of concern", or "bad". We also graphically compared the density of each control variable with its density in the corresponding control group for each model.

Table 5. Results (odds ratios) for logit models that characterize BEV households.

	BEV-Only		BEV+	
	Multi-States N = 32,558	**CA N = 23,079**	**Multi-States N = 36,851**	**CA N = 23,268**
Generations in the household				
Silent Generation	**0.095** *	**0.117** *	0.616	**0.578** *
Baby Boomer	**0.138 †**	**0.184** *	0.904	0.94
Generation X	0.547	0.593	1.091	1.009
Generation Y	0.220	0.342	**0.688** *	0.759
Generation Z	- -	- -	1.133	1.243
Household structure				
1 adult, no children	0.996	- -	**0.238 ‡**	0.603
1 adult, some children	1.286	- -	0.438	0.818
2+ adults, some children	1.296	- -	1.240	1.414
1 retired adult, no children	- -	- -	**0.094 †**	0.406
2+ adults, some children	- -	- -	**0.615** *	0.700
1+ retired adult(s), no children	5.284	- -	- -	- -
1 adult, possibly with children	- -	0.299	- -	- -
2 adults, possibly with children	- -	0.326	- -	- -
Household size	0.850	1.013	0.933	0.929
Number of household workers	**2.736 †**	1.725	0.890	0.978
Household race				
African American/Black	- -	- -	0.568	0.836
Asian	- -	- -	1.275	**1.652 ‡**
Others	- -	- -	0.744	1.050
Non-White	**2.846 †**	**2.852 †**	- -	- -
Hispanic	1.979	0.796	**0.475** *	0.665
Household annual income				
USD 25,000 to USD 49,999	- -	- -	0.500	1.923
USD 50,000 to USD 74,999	- -	- -	0.744	2.473
USD 75,000 to USD 124,999	**4.080** *	0.579	1.528	**4.213** *
USD 125,000 or more	**18.817 ‡**	**13.200 ‡**	**2.499** *	**9.025 ‡**
Household education				
Bachelor's degree	0.377	0.462	**1.838** *	**2.202†**
Graduate or professional degree	0.603	0.618	**4.274 ‡**	**4.124 ‡**
Homeownership	1.628	**2.375** *	**1.725 †**	**1.982 ‡**
Number of household drivers	**0.333 †**	**0.349** *	1.252	1.105
Number of household vehicles	**0.139 ‡**	**0.105 ‡**	**1.289 ‡**	**1.285 ‡**
Population density (persons/mi^2):				
0–99	- -	- -	3.720	1.649
100–499	- -	- -	3.954	1.074
500–999	- -	0.459	**5.233** *	1.307
1000–1999	2.034	0.46	4.621	1.458
2000–3999	**3.178** *	0.925	4.643	**1.825** *
4000–9999	1.062	0.482	3.482	1.628
10,000–24,999	- -	- -	1.884	0.992
Household lives in Georgia (GA)	2.184	- -	1.513	- -
Household lives in New York (NY)	- -	- -	**0.271 ‡**	- -
Household lives in Texas (TX)	0.668	- -	**0.413 ‡**	- -
Charging stations per 100 K persons	**1.115 ‡**	- -	**1.124 ‡**	- -

*: $p < 0.10$; †: $p < 0.05$; ‡: $p < 0.01$. "- -" indicates that a variable was not included in a model. Statistically significant results are in bold, so they are easier to spot. Wald χ^2 (degrees of freedom) for BEV-only multi-states, BEV-only CA, BEV+ four-state, and BEV+ CA models are 461.6 ‡ (25), 404.0 ‡ (21), 478.8 ‡ (36), and 344.9 ‡ (32), respectively. The corresponding pseudo-R^2 values are 0.246, 0.228, 0.212, and 0.150, respectively. The small number of BEV-only households (see Table 2) required combining variables describing household structure, race, income, and population density and dropping the binary variable describing the presence of Gen Z household members.

5. Results

We used Stata 17 on a desktop computer to perform our statistical analyses. In the following, we first present logit model results that are building blocks of PSM, before discussing our PSM results.

5.1. Logistic Regression Results Examining BEV+ Households

As explained in Section 4, PSM relies on propensity scores estimated (here) via logit models. Since these models characterize BEV households, it is useful to examine their results, which are presented in Table 5 in the form of odds ratios (denoted by OR). When OR > 1 for an explanatory variable, that variable is associated with higher odds of being a BEV household; when OR < 1, the reverse holds. As pointed out by one of our reviewers, no causation can be inferred for the results shown in Table 5.

The four models presented in Table 5 do not have the same explanatory variables. The small number of BEV-only households (see Table 2) required combining variables describing household structure, race, income, and population density and dropping the binary variable describing the presence of Gen Z household members.

Starting with BEV-only households in the multi-state sample, households with Silent Generation members (OR = 0.095 *) and Baby Boomers (OR = 0.138 †) are less likely to be BEV-only. Conversely, having more workers in the household increases the likelihood of being BEV-only (OR = 2.736 †), possibly because it increases household income (OR = 18.691 ‡). Education variables are not significant, however. BEV-only households are also more likely to be non-White (2.846 †). The number of household drivers (0.333 †) and the number of household vehicles (0.139 ‡) matter, but mostly because BEV-only households are less likely to have multiple vehicles. The only other statistically significant variables are one density variable (OR = 3.178 *) and the number of charging stations per 100,000 persons in the CBSA of residence (1.115 †).

BEV-only results for California are similar, with some nuances. Although homeownership matters (OR = 2.375 *), population density and the number of public chargers do not—we tried several models and present the "best" models based on BIC, the Bayesian information criterion, possibly because of the relative ubiquity of public charging stations around the residence of California BEV-only households in our sample. We urge caution when interpreting these results because of the small number of BEV-only households in our sample (25 for the four-state sample and 23 in California, although some of these 23 are not in the four-state sample because of missing values for charging stations).

Results for BEV+ households have some similarities with those for BEV-only households, but they also differ in important ways, partly because the number of BEV+ households is substantially larger.

Starting with the multi-state sample, households with Gen Y members are less likely to own a BEV (OR = 0.688 *), partly because age effects are reflected via some household structure variables: households with only one retiree and no children (OR = 0.094 †) are less likely than households with two adults without children (our baseline) to be in the BEV+ category, and so are those with one adult and no children (0.238 ‡), or with at least two adults with children (OR = 0.615 *). Race does not matter in this scenario, but people who are Hispanic are less likely to be BEV+ households (OR = 0.475 *). As for BEV-only households, higher income households are more likely to own a BEV (OR = 2.499 *) in addition to an ICEV, but now education also plays a role (e.g., OR = 4.274 ‡ for "graduate or professional degree"), which is in agreement with previous studies [19,32,36,38,40]. Homeownership also helps (OR = 1.725 †) [33,51], and so does having more household vehicles (OR = 1.289 ‡). Somewhat surprisingly, only one population density variable is significant. Compared to California, Texas (OR = 0.413 ‡) and even more so New York (OR = 0.271 ‡) households with otherwise similar characteristics are less likely to be BEV+. Lastly, the number of charging stations per 100,000 residents is positively associated with BEV+ household status (OR = 1.124 ‡).

California results for BEV+ households are mostly similar to those for the multi-state sample, but there are a few differences. First, only households with Silent Gen members are less likely to have both BEVs and ICEVs, and household structure does not come into play. Second, Asian households are more likely to be BEV+ households (OR = 1.652 ‡). We conjecture that one underlying reason is the wealth of Asian households: in Los Angeles County, for example, the top three groups in 2014 for household median net worth were people of Japanese (USD 592,000), Asian Indian (USD 460,000), and Chinese (USD 408,200) ancestry (the median net worth of White households was USD 355,000) [57]. Income matters even more, and statistical significance starts at lower income levels. As for the four-state sample, more education makes a difference, and so does home ownership, but various measures of charging station availability (competing models were eliminated based on BIC).

5.2. PSM Results

Here, we use PSM to calculate the statistical significance of the difference after matching (Equation 3 in Section 4) between a measure of travel (annual mileage, number of trips, daily travel time, or daily travel) of household vehicles for either BEV-only or BEV+ households and non-BEV households. A significant negative number indicates that non-BEV households drive more, and a significant positive number means the reverse. We relied on the Stata command "teffects psmatch" because unlike "psmatch2", it reflects that propensity scores are estimated (not known) when calculating standard errors.

Results presented below all verify the balancing condition, which we checked using "pscore" in Stata 17. We also used "pstest" after "psmatch2" (to the best of our knowledge, similar tools are not available after "teffects psmatch" yet), which gave us various measures of overall imbalance, including the estimated mean and median bias in the distributions of the treatment and control groups, and the percentage of continuous variables that are of concern and that are "bad"[56]. We obtained the best matching results for the samples with the largest number of BEV households (BEV+ households for annual mileage and weekday travel for the four-state sample).

5.2.1. Analysis of Annual Mileage

The top half of Table 6 indicates that BEV-only households drive less than non-BEV households, although this difference is significant only in California (−4004.4 *). This is not the case for BEV+ households, particularly when we jointly analyze households in California, Georgia, New York, and Texas. These conclusions still hold qualitatively (bottom half of Table 6) when we trim the top and bottom 1% of households based on mileage (i.e., after dropping households who drove less than 200 mi or more than 85,000 mi per year), but the magnitude of the difference between households with BEVs and those without changes. However, the lack of statistical significance can be partly attributed to our relatively small sample size (particularly for BEV-only households; see Table 2).

Table 6. PSM results for annual mileage analysis.

	Multi-States	**CA Only**
Untrimmed sample		
BEV-only vs. non-BEV households	−1185.4	**−4004.4 ***
BEV+ vs. non-BEV households	61.7	−1023.1
Trimmed sample (removed top and bottom 1%)		
BEV-only vs. non-BEV households	−111.1	**−3011.5 ***
BEV+ vs. non-BEV households	−1070.8	−1302.6

* $p < 0.1$. Statistically significant differences are in bold so they are easier to spot. For BEV-only households, our sample includes only residents from CA, GA, and TX because of the very small number of BEV-only households in NY. For BEV+ households, our sample includes residents from CA, GA, NY, and TX.

For BEV+ households, it is also of interest to understand what fraction of household VMT comes from BEVs versus conventional vehicles. Figure 2 shows that BEV+ households tend to drive their BEVs less than their conventional vehicles (the bottom five bins comprise over 59% of BEV+ households), possibly because they rely on conventional vehicles for longer trips. The next sub-section explores how this translates into daily VMT.

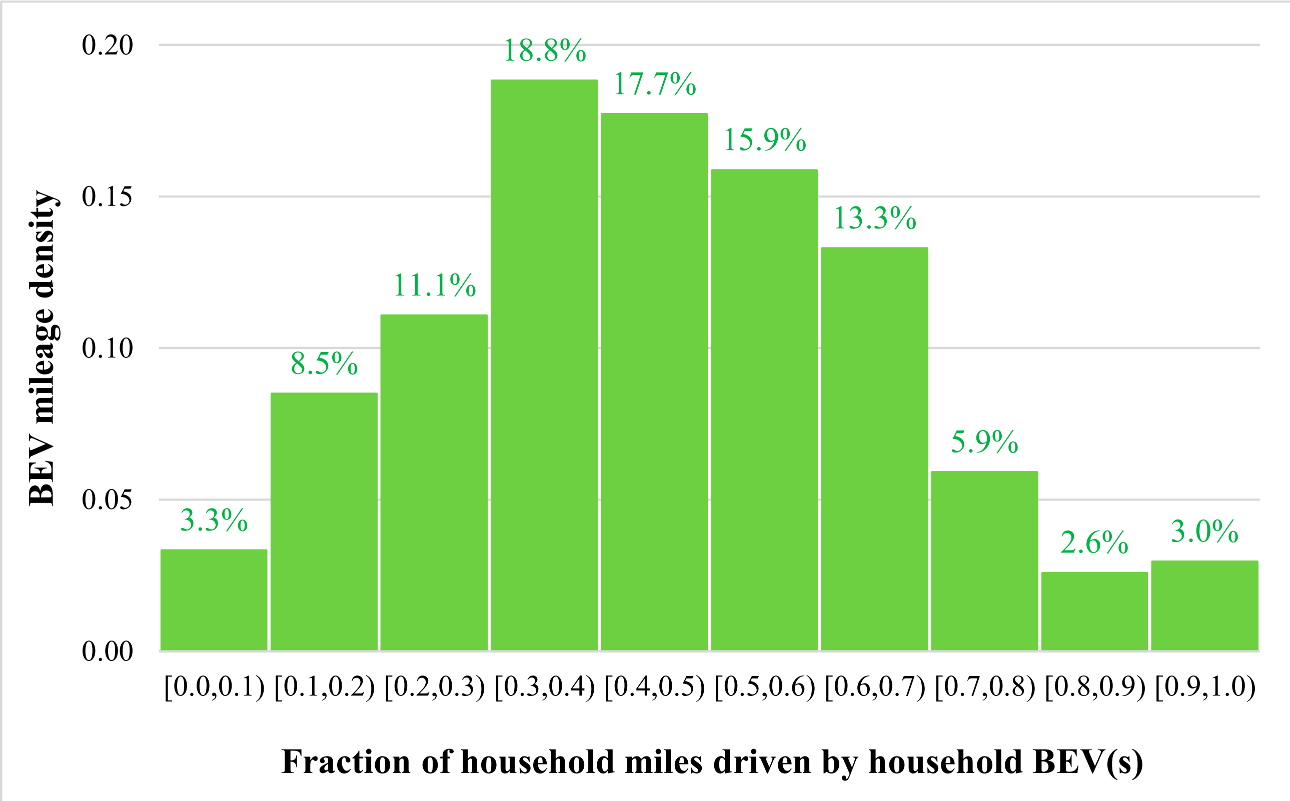

Figure 2. Distribution of within household VMT for BEV+ households.

5.2.2. Comparing Travel between BEV and Non-BEV Households Using PSM

Next, we examine various measures of travel and contrast weekday versus weekend daily travel. We present results for our four-state sample (CA, GA, NY, and TX) and for California. The samples of BEV-only and BEV+ households from just GA, NY, and TX were too small to yield dependable results. Likewise, the number of BEV-only households whose travel day was on a weekend was too small to meet the balancing condition.

Table 7 presents PSM results for general trip characteristics (number of trips, trip distance, trip duration). Panel A compares BEV-only to non-BEV households, and Panel B contrasts BEV+ with non-BEV households.

Let us first contrast weekday trips of BEV-only and non-BEV households for weekday trips. Panel A of Table 7 shows that, except for daily travel time in California, there are no statistically significant differences between these two groups of households. Reasons why California BEV-only households drove less than similar non-BEV households (they took 1.42 fewer daily trips on average, which saved them 26.7 min as they drove 7.4 fewer miles) are discussed below when we consider trip purposes.

Panel B of Table 7 suggests that the travel behavior of BEV+ households in California differed from those in Georgia, New York, and Texas. In both cases, they took more trips (0.62* in the aggregate sample comprised of CA, GA, NY, and TX, vs. 0.98† in California alone) than similar non-BEV households, but overall, BEV+ households traveled 9.1 fewer miles (saving 15.5 min), whereas BEV+ Californians drove an additional 4.4 miles daily (and 8.3 min on the road).

Table 7. PSM results for general trip characteristics using household vehicles.

	Weekday	Weekend	Weekday	Weekend
Panel A: BEV-only vs. non-BEV households	CA, GA, TX		CA	
Daily number of trips	−0.03	--	−1.42	--
Daily travel time (in minutes)	7.6	--	**−26.7 ***	--
Daily travel distance (in miles)	9.1	--	−7.4	--
Panel B: BEV+ vs. non-BEV households	CA, GA, NY, TX		CA	
Daily number of trips	**0.62 ***	0.46	**0.98 †**	0.36
Daily travel time (in minutes)	−15.5	19.6	8.3	14.3
Daily travel distance (in miles)	**−9.1 ***	13.3	4.4	15.5

* $p < 0.1$; † $p < 0.05$. Statistically significant differences are in bold for better legibility. In Panel A, the number of BEV-only households who traveled on the weekend in the NHTS is too small to apply PSM. More generally, PSM results for BEV-only households should be treated cautiously because of the small number of these households in the 2017 NHTS.

To further inquire about some of the differences observed above, we considered trip purposes (Panel A, Table 8). Starting with our multi-state sample, we see that BEV-only households (although not for the California subsample) took slightly more work trips (0.3*) on weekdays and drive on average 7.2* more miles. However, they took fewer daily shopping trips (−0.5‡ for the four-state sample, −0.8‡ for California) on weekdays, which reduced their daily travel time (by 7.0† minutes on average, 7.9† in California) and distance (−2.3 mi overall, although it is not significant, and −2.8† in California). California BEV-only households took slightly fewer trips to purchase meals, which saved them 4.0† miles per day on weekdays. The number of weekend trips was too small to contrast BEV-only and non-BEV households.

Table 8. PSM results by travel purpose when using household vehicles.

Trip Purpose	Multi-State Sample: Number of Trips	Multi-State Sample: Travel Time (min)	Multi-State Sample: Travel Distance (mi)	California: Number of Trips	California: Travel Time (min)	California: Travel Distance (mi)
Panel A: Weekday travel for BEV-only vs. non-BEV households						
Work	**0.3 ***	9.2	**7.2 ***	−0.1	−0.9	4.0
School/daycare/religious	0.0	0.5	0.2	0.0	−2.2	−1.6
Medical/dental services	0.1	**1.8 ‡**	0.5	0.0	**0.0 ‡**	**0.0 ‡**
Shopping/errands	**−0.5 ‡**	**−7.0 †**	−2.3	**−0.8 ‡**	**−7.9 †**	**−2.8 †**
Social/recreational	0.1	−0.5	−1.0	0.2	−2.0	−2.9
Transport someone	0.1	**3.4 ***	2.8	0.1	3.6	3.2
Meals	0.0	−1.8	−1.8	−0.1	−7.2	**−4.0 †**
Panel B: Weekday travel for BEV+ vs. non-BEV households						
Work	0.0	−5.2	−2.0	0.1	1.2	1.3
School/daycare/religious	0.0	0.0	−0.3	0.0	−0.4	−0.5
Medical/dental services	0.0	−0.2	−0.5	0.0	0.7	0.2
Shopping/errands	0.0	−1.7	−1.6	0.1	−0.3	−1.0
Social/recreational	0.0	−1.2	−0.7	0.0	−2.9	−2.0
Transport someone	0.2	0.7	0.6	**0.3 †**	**5.9 †**	**3.2 ‡**
Meals	0.0	**−2.9 ***	**−1.8 ***	0.1	−0.2	−0.6

Table 8. *Cont.*

Trip Purpose	Multi-State Sample: Number of Trips	Multi-State Sample: Travel Time (min)	Multi-State Sample: Travel Distance (mi)	California: Number of Trips	California: Travel Time (min)	California: Travel Distance (mi)
Panel C: Weekend travel for BEV+ vs. non-BEV households						
Work	0.0	−0.7	−0.6	**−0.1 ‡**	−3.1	**−2.7 ***
School/daycare/religious	**0.2 ***	2.3	1.4	**0.2 †**	**2.8 †**	**1.4 †**
Medical/dental services	0.0	0.2	0.0	0.0	0.5	0.1
Shopping/errands	0.0	−0.6	1.0	−0.2	−1.0	1.2
Social/recreational	0.0	7.1	6.3	**0.4 †**	10.5	10.9
Transport someone	0.2	3.1	**2.0 ***	0.1	1.0	0.4
Meals	−0.1	−0.9	−1.5	0.0	0.6	0.8

* $p < 0.1$; † $p < 0.05$; ‡: $p < 0.01$. Statistically significant differences are in bold so they are easier to spot.

More robust results are available for BEV+ households. Starting with weekday travel (Panel B of Table 8), we observe only a couple of travel differences with non-BEV households. First, BEV+ households traveled a little less to purchase meals (−1.8 * miles per day on average, which saved them 2.9 * minutes), and second, California BEV+ households were more likely to transport someone (+0.3 † trips per day, which required 5.9 † minutes for 3.2 ‡ additional miles).

Differences in weekend travel between BEV+ and non-BEV households are similarly limited. We just note slightly more trips (0.2 * per day) for school/daycare/religious activities and for driving someone (0.2 day, resulting in 2.0 * extra daily miles). There are a few more differences in the California subsamples. In addition to 0.2 † trips per weekend day for school/daycare/religious activities, California BEV+ households took 0.1 ‡ fewer work trips, and 0.4 † more weekend trips for social or recreational activities.

From Table 8 results, BEV-only households relied more on e-shopping (online shopping with home delivery) and meal deliveries, possibly because they were more technology savvy. We conjecture that the discrepancy between our analysis of daily and annual mileage is partly due to the under-reporting of longer, less frequent trips, which are not well captured by questions about daily travel, because the charging infrastructure in the U.S. was still under-developed in 2016–2017 and likely discouraged longer BEV trips.

Finally, we note that differences in our results between BEV-only and BEV+ households underline the need to separate these two groups of households when analyzing travel behavior.

6. Conclusions

In this paper, we analyzed the 2017 NHTS using propensity score matching, a quasi-experimental method, to contrast how early adopters of battery electric vehicles traveled compared to households who only have access to conventional vehicles.

Our results show that BEV-only households were less likely to have members of older generations, and more likely to be non-White (here, mostly Asian) with a higher annual income, and to own their home. Overall, BEV-only households did not drive significantly less than non-BEV households, except in California. We also found no statistical differences in the number of daily trips, travel time, or travel duration, except for California BEV-only households who took almost 1.5 fewer daily trips (this difference is not significant) and spent on average almost 27 fewer minutes driving. Differences in daily travel include taking a few more trips to work on weekdays, resulting in 7.2 extra daily miles, but fewer trips for shopping. The small number of BEV-only households in our sample did not allow us to assess differences in weekend travel.

BEV+ households were less likely to have only one adult or to include children. In California, they were more likely to be Asian. They were also more likely to have an annual income over USD 75,000, at least a college education, and to own their home. Compared to non-BEV households, we found no statistically significant differences in their annual VMT. On average, they took slightly more daily trips, although their daily VMT was lower by 9.1 miles in our multi-state sample. We found, however, very few differences in their weekday or weekend travel compared to non-BEV households.

We conjecture that the apparent discrepancy between annual mileage and the daily mileage analyses is due to infrequent long-distance trips, which are often poorly captured by daily travel surveys. Taking these trips with BEVs in 2017 would have been a challenge because of charging infrastructure limitations. The challenges for early BEV adopters to take long distance trips has led some researchers (e.g., see [58] for Sweden and Germany, or [59] for Sweden) to suggest that early BEVs may have been better suited as second cars for multi-car households.

Moreover, differences between BEV households in California and the rest of the country may be partly driven by stronger environmental beliefs about the need to address global climate change coupled with more favorable attitudes toward new technology (Google, Apple, and Facebook are based in California, and Tesla used to have its headquarters in the Golden State). California has been at the forefront in addressing climate change in the U.S., as illustrated by Executive Order N-79-20 that mandates 100% zero-emission new light-duty vehicle sales by 2035.

Overall, our results align with microeconomic theory: since EVs have a lower marginal cost of driving compared to ICEVs, BEV owners drive at least as much as ICEV owners unless they have concerns about their ability to conveniently recharge their BEVs. Our findings also outline the value of using quasi-experimental research designs in transportation, such as PSM, to tease out causal impacts. Although our results are specific to the United States at the time of the 2017 NHTS, our methodology is widely applicable.

As mentioned in the introduction, understanding BEV household travel behavior, including for specific purposes, is important to transportation planners and policymakers so they can better plan the transition to EVs and proactively address unintended effects, such as the risk of a sharp increase in VMT. A cursory overview suggests that key limitations of current BEVs are vanishing, thanks to the development of fast charging [60,61], the expansion of the charging infrastructure [62,63], and the arrival of purchase price parity with ICEVs as the mass production of BEVs ramps up [64]. Fast charging, in particular, is seen by many researchers and policymakers as the key to significantly increase the appeal of BEVs to more mainstream consumers once the charging infrastructure is sufficiently developed [61,65,66]. Fast charging also provides the added benefit of reducing vehicle weight, thus reducing the wear of traffic on the road infrastructure. Hence, unless the incentives to purchase BEVs are cut sharply and prematurely, the price of fossil fuels unexpectedly plummets, or the federal government throttles excessively the importation of BEVs that keeps the pressure on US automakers to innovate, we can expect the VMT from BEVs to soon exceed the VMT of ICEVs in comparable households.

A number of strategies that have been proposed to reduce VMT [67,68] still apply to a world where BEVs have replaced ICEVs. They involve improving alternatives to driving (e.g., transit and active mode improvements, promoting carsharing), creating programs with employers and schools (e.g., promoting telework, creating trip reduction programs, or offering free or reduced transit pass programs), implementing pricing policies (e.g., tolls road, congestion and/or cordon pricing, pricing parking, and creating mileage-based fees possibly while taking into account vehicle weight to capture damage to roadways or mileage-based insurance), and fostering smart growth and other land use planning approaches (e.g., transit oriented development, switching to complete streets, job–housing balance). A combination of positive (e.g., developing alternatives to driving) and negative (pricing or restrictions) incentives has shown to be effective if there is enough political will to implement unpopular measures (e.g., pricing).

Some regulatory changes can also help. In California, Senate Bill 743 (SB 743), which came into effect July 1, 2020, requires cities to evaluate the impacts of real estate and transportation projects using VMT (instead of level of service, LOS) to reduce emissions of GHG and of air pollution, and promote the development of multimodal transportation networks. By contrast, the LOS metric burdened last-in infill developments, encouraged sprawl, and favored personal vehicles over active modes and transit, leading to more GHG and air pollutant emissions.

Moreover, the recently approved Advanced Clean Cars II rule will require all new passenger cars, trucks, and SUVs sold in the state to be zero-emission by 2035 [69]. These new regulations have national importance for two reasons: first, because California is the largest auto market in the U.S., and second because Section 177 of the Clean Air Act allows other states to adopt California's motor vehicle emission standards without seeking EPA approval [70]. A large increase in EVs could potentially strain the electrical grid and require substantial infrastructure investments to handle the increased demand for electricity, in addition to the need for building a robust charging infrastructure for EVs.

It is now well understood that the replacement of ICEVs with BEVs coupled with the production of renewable electricity (e.g., from sunlight or the wind) are essential to reduce the GHG emissions from the transportation sector. However, if (as expected) EVs are driven more than ICEVs, their arrival will increase VMT, energy demand, congestion, and possibly accidents since BEVs can typically accelerate more briskly than similar ICEVs (unless new safety technologies are sufficiently disseminated). As our findings confirm that simply transitioning to EVs is not going to reduce VMT (in fact, it is likely to increase VMT if no other policy is put in place), it is important that transportation planners and policymakers consider implementing some of the measures presented above.

Our work is not without limitations. As we focused on early adopters by analyzing 2017 data, the number of BEVs in our dataset is relatively small, which prevented us, for example, to analyze weekend travel for BEV-only households. The lack of information about charging stations in many parts of the country and the paucity of location information also limited our analysis. The lack of questions about attitudes or expectations in the 2017 NHTS, which are partly inherent to cross-sectional datasets, may have prevented PSM from yielding completely biased-free results.

Fruitful avenues for future research include applying our approach to other datasets collected at different points in time and in different parts of the world to monitor how much BEVs are driven as battery technology improves, the charging infrastructure expands, fast-charging becomes more common, and BEV prices reduce. Some of these datasets will hopefully include data about attitudes and possibly have a panel structure to capture change and help remove unobserved variables. Another promising area of research is to explore how BEVs fit with other household travel modes, including transit and active transportation. Future research could also examine detailed trip purpose as a more diverse set of households gains access to BEVs and explore who benefits most from replacing diesel trucks with zero-emission heavy duty vehicles. More generally, more research is needed to understand how market incentives could best be used to foster the adoption of BEVs (e.g., see [71]), quantify the environmental benefits of BEVs [72], plan the expansion of the charging infrastructure (e.g., see [73] for fast-charging, or [74] for electric roads), and explore how BEV use could interact with the electric grid [75]. Qualitative analyses via interviews of focus groups (e.g., see [76,77]) could provide some useful starting points before undertaking quantitative analyses.

In closing, we concur with [78] that the literature on BEV adoption and use would benefit from adopting methods that allow teasing out causality (as we have attempted to do here), and provide more information about study design while making available the data analyzed.

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