AEA Papers and Proceedings 2021, 111: 430–435
https://doi.org/10.1257/pandp.20211088

THE ELECTRICITY GRID OF THE FUTURE‡

Low Energy: Estimating Electric Vehicle Electricity Use†

By Fiona Burlig, James Bushnell, David Rapson, and Catherine Wolfram*

Policymakers attempting to guide transportation electrification lack credible estimates of one of the most important pieces of information: how much electric vehicles (EVs) are actually being used. This blind spot exists because of data limitations. The vast majority of EV charging occurs at home, where it is difficult to distinguish from other end uses on the home's master electricity meter. Until now, published estimates of residential EV load are either survey based or extrapolated from a small, unrepresentative sample of households with dedicated EV meters. As a result, industry participants and regulators alike may have inaccurate beliefs about the private and social costs and benefits of EVs.

EV electricity consumption provides a measure of the promise of EV technology as a potential replacement for the conventional gasoline car. If EVs are being driven as much as conventional cars, it speaks to their potential as a near-perfect substitute to vehicles burning fossil fuels. If, on the other hand, EVs are being driven substantially less than conventional cars, it raises important questions about the potential for the technology to replace a vast majority of trips currently using gasoline. Ideally, policymakers would have a more complete picture about the role EVs play in a region's transportation portfolio before costly and irreversible commitments are made to the technology as the primary solution to the decarbonization of transportation.

In this paper, we present the first at-scale estimates of residential EV charging load in California, home to approximately half of the EVs in the United States (Davis 2019). Our estimates are derived from a sample of roughly 10 percent of residential electricity meters in the largest utility territory, Pacific Gas and Electric (PG&E), which we merge with address-level data on EV registration records from 2014–2017. We deploy standard event study and difference-in-difference methods to estimate the change in overall household electricity load around EV registration events.

Our estimates indicate that EV load in California is surprisingly low. We find that adopting an EV increases household electricity consumption by 0.12 kilowatt-hours (kWh) per hour, or 2.9 kWh per day. These estimates are substantially lower than official EV driving estimates used in regulatory proceedings (see, e.g., Joint Utilities 2019). The discrepancy between the estimates likely results from selection bias in the official estimates, which are extrapolated from a very small number of households that have installed dedicated EV meters. Given the fleet of EVs in our sample, and correcting for the share of out-of-home charging, our estimates translate to approximately 1,700 electric vehicle miles traveled (eVMT) per year for plug-in

‡*Discussants:* Ashley Langer, University of Arizona; Mar Reguant, Northwestern University; Tatyana Deryugina, University of Illinois.

* Burlig: Harris School of Public Policy and Energy Policy Institute, University of Chicago and NBER (email: burlig@uchicago.edu); Bushnell: Department of Economics and Davis Energy Economics Program, UC Davis and NBER (email: jbbushnell@ucdavis.edu); Rapson: Department of Economics and Davis Energy Economics Program, UC Davis (email: dsrapson@ucdavis.edu); Wolfram: Haas School of Business and Energy Institute at Haas, UC Berkeley and NBER (email: cwolfram@berkeley.edu). We gratefully acknowledge funding from the State of California Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1) via the University of California Institute of Transportation Studies. This study has IRB approval from the UC Berkeley Committee for Protection of Human Subjects under Protocol Nr. 2017-10-10430. Jesse Buchsbaum, Benjamin Dawson, Shelly He, Ellen Lin, and Pengyu Wang provided excellent research assistance. Karen Notsund provided invaluable data support. All errors are ours.

† Go to https://doi.org/10.1257/pandp.20211088 to visit the article page for additional materials and author disclosure statement(s).

hybrid EVs (PHEVs) and 6,700 eVMT per year for battery EVs (BEVs). These eVMT values are substantially less than internal combustion engine (ICE) VMT, suggesting that electricity may not be as easily substituted for gasoline as previously thought.

I. Setting and Data

The California Energy Commission projects that EVs will account for almost all of the expected growth in electricity demand over the next decade (California Energy Commission 2018). The timing and magnitude of EV load will be crucial factors in determining how electricity markets will be affected by transportation electrification. The profile of residential load is already changing rapidly as a result of investments in behind-the-meter solar generation, and EV charging may further alter the residential load profile. The timing of EV-related electricity demand will affect both the economic value of the energy consumed and marginal emissions. Further, the price responsiveness of EV loads informs the extent to which policymakers can shift charging behavior, and within-neighborhood correlations in charging should influence decisions about utility system planning in the near future.

By far the largest challenge in evaluating the economic and environmental impact of EVs to date has been the lack of quality data about either their energy demand or vehicle utilization. Absent data at scale, researchers and policymakers have been forced to rely upon survey or measurement data from small, selected samples.[1] The resulting estimates vary widely. Using data from the 2017 National Household Travel Survey, Davis (2019) estimates that pure battery electric vehicles are driven less than two-thirds the miles of conventional cars and less than half the miles of conventional hybrids. However, a survey by the UC Davis Plug-In Hybrid & Electric Vehicle Research Center finds eVMT numbers almost double those cited by Davis (2019) (Tal et al. 2020).

As an alternative to using survey data, another method for estimating eVMT is to extrapolate miles from the electricity used in EVs. However, an EV can be charged using an ordinary household electricity connection and does not require a separate meter, or even separate equipment, for low-voltage charging. Consequently, less than 5 percent of EVs are directly metered when charging at home (Joint Utilities 2019). While charging at networks operated either by commercial charging businesses or vehicle manufactures such as Tesla is directly metered, the California Air Resources Board estimates that upwards of 85 percent of EV charging occurs at home (California Air Resources Board 2020). Thus, the vast majority of EV charging is currently unmeasured. To form projections of future electricity use, however, California state agencies utilize measurements from the small share of EVs that *are* directly metered. Of course, if charging via these meters is not representative, this may paint a very inaccurate picture of true home EV charging in the population. For example, households that install EV-specific meters may be wealthier, buy cars with bigger batteries, or simply be more inclined to use their cars more.

We assemble household-level data from two main sources: electricity meter data from a 10 percent sample of PG&E's residential customers and EV registration data from the California Department of Motor Vehicles (DMV). For more details on these data, see Burlig et al. (2021).

A. *Electricity Meter Data*

We obtained three types of data from PG&E: monthly billing information, hourly electricity consumption data, and customer details. In addition to the consumption and billing data, we observe each customer's street address, latitude and longitude, rate class, and solar panel interconnection date where applicable. In order to maximize the number of EVs in the dataset, the sampling frame overweights households in census block groups that have high EV penetration. The sample consists of 362,945 households and over 1.7 billion hourly electricity consumption observations. We observe that EV households are much more likely to have solar, have multiple electricity meters, and consume more electricity per hour. They also have higher bill consumption and bill amounts than their non-EV-owning counterparts.

[1] The best data on EV charging use are likely within the vehicles themselves. Most Original Equipment Manufactures (OEMs) collect charging data from the cars they have sold, but these data are held closely due to strategic business interests and privacy concerns.

B. *EV Registration Data*

We obtained California DMV registration records for the period 2008 to 2019. Our dataset contains the universe of EVs registered in the state during this time period. For each EV, we observe the address, make, model, year, seven-digit VIN stem, registration date, and a set of vehicle attributes. We also observe an anonymized unique vehicle identifier that allows us to track vehicles over time. We observe 423,297 unique vehicles in the state of California during this period, 74,468 of which are in zip codes belonging to the sample of the PG&E service territory that matches our analysis sample. Of these, 63,765 are in the PG&E service territory between 2014 and 2017, the time period of our electricity-use information.

C. *Matching*

We use a string matching algorithm to assign EVs to PG&E households. We begin by cleaning the data so that common words are represented in the same way in both datasets (e.g., "ave" versus "avenue," "st" versus "street," etc). Next, we perform an exact match on address. We use a fuzzy string match to finalize our merge. Out of the more than 63,000 vehicles registered in zip codes in our main PG&E analysis sample, we matched 57,290 cars to PG&E addresses, a match rate of 89.8 percent.[2]

II. Empirical Design and Results

With access to this unique dataset on both electricity use and EV registration, we are able to empirically estimate the effects of EV ownership on residential energy use among this large sample of PG&E households.

A. *Estimation*

To quantify EV usage, we estimate the causal effect of EV adoption on residential energy consumption using a panel fixed effects research design. We use a simple specification as the basis for our analysis:

$$(1) \quad Y_{ith} = \beta EV_{it} + \gamma Solar_{it} + \alpha_i + \delta_t + \varepsilon_{ith},$$

where Y_{ith} is electricity consumption (measured in kWh per hour) in household i during week-of-sample t in hour-of-day h.[3] Here, EV_{it} is a count of the number of EVs registered to household i in week t, and it is equal to zero for households without EVs. The variable $Solar_{it}$ is an indicator equal to one if household i has installed solar panels by week t and zero otherwise, which we include because approximately 20 percent of the EV-owning households in our sample also have solar panels. Failing to control for this could bias our results toward zero, as installing solar reduces net electricity demand.[4] Further, α_i are household-by-year and household-by-month-of-year fixed effects, and δ_t are week-of-sample fixed effects. Our results are robust to using more parsimonious fixed effects, including using only household fixed effects alone (see Burlig et al. 2021 for additional robustness). The variable ε_{ith} is an error term, which we two-way cluster at the census block group and week-of-sample levels. Here, we present two extensions to this main specification: an event study approach, where we estimate separate β and γ coefficients for the 25 weeks before and after an EV is registered and/or solar panels are installed at a household, and an hourly treatment effects approach, where we estimate separate β and γ coefficients for each hour of the day. We also explore heterogeneity by EV type: Teslas, plug-in hybrid EVs (PHEVs), and non-Tesla battery EVs (BEVs).

B. *Identification*

In order for this approach to capture the causal effect of EV adoption on household electricity use, we require that households that adopted EVs would have remained on a similar counterfactual trend to nonadopting households

[2] Some of the remaining addresses belong to municipal and other local utilities that share zip codes with PG&E, so we would not expect them to match to PG&E addresses.

[3] We collapse the data to the household $\times$ week-of-sample $\times$ hour-of-day level to speed computation time; results using the full daily data would be similar but substantially slower to estimate (Burlig et al. 2020).

[4] One concern in this setting is measurement error in treatment dates: if the DMV registration records or PG&E solar installation are misaligned with actual adoption, our treatment effect estimates will be attenuated. Therefore, our preferred specification uses a "donut" approach, where we drop the four weeks before and after EV and/or solar adoption for each household.

in the absence of EV adoption, after controlling for our rich set of fixed effects. We provide two main pieces of evidence in favor of this assumption: First, we show in the left panel of Figure 1 that prior to EV adoption, there is a flat pretrend. Second, as the right panel of Figure 1 shows, our treatment effects are concentrated in the evening hours, consistent with survey evidence about EV charging patterns (Davis 2019). In order for our results to be explained by contemporaneous changes in electricity use other than EV adoption, these changes would need to only impact household energy use during evening hours, an unusual load profile for most appliances.

C. *Main Results*

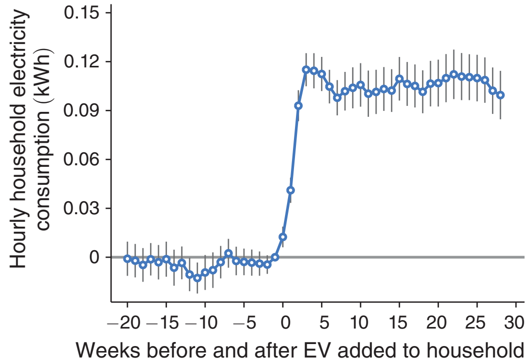
We find that adopting an EV increases a household's electricity consumption by 0.121 kWh per hour (SE 0.007, $p < 0.01$), or approximately 2.9 kWh per day. The top panel of Figure 1 presents this result in the form of an event study.[5] This figure has several notable features. First, prior to EV adoption, the energy-use pretrend is very flat, providing support in favor of our identifying assumption. Second, we see a sharp increase in household use when a household adds an EV. Finally, we see that our treatment effect is quite stable up to 25 weeks after EV adoption.

D. *Heterogeneity*

Next, we present heterogeneous effects along two dimensions. The bottom panel of Figure 1 shows the effect of EV adoption on household electricity use for each hour of the day, separately by vehicle type.

We find that our EV treatment effects are concentrated between 10 PM and 6 AM. This is consistent with households charging their EVs when they come home and leaving them plugged in over night. This hourly pattern has environmental implications, as marginal emissions on the electricity grid vary with hour of the day (Holland et al. 2016). In California, marginal emissions are highest overnight, when the marginal electricity generator is likely to be gas fired.

[5] In this event study, we set $t = 0$ as 4 weeks prior to the registration date, because car dealers have up to 20 days to submit registration information to the DMV and the DMV takes 8–10 business days to process registrations.



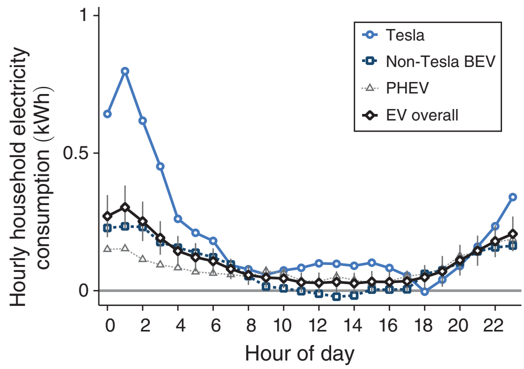


FIGURE 1. IMPACTS OF EV ADOPTION ON HOUSEHOLD ELECTRICITY USE

Notes: This figure presents our estimates of the impact of EV adoption on household electricity consumption. The top panel plots the event study version of equation (1). Household electricity use clearly rises in response to EV registration. This plot also indicates that there is mismeasurement in EV registration dates. The bottom panel plots difference-in-difference estimates by hour of day and vehicle type. We plot separate estimates for Teslas, non-Tesla BEVs, and PHEVs as well as overall estimates using all EVs. In both plots, 95 percent confidence intervals are in gray. Standard errors are two-way clustered at the census block group and week-of-sample level.

The bottom panel of Figure 1 also presents separate treatment effects for three vehicle types: Teslas (the modal manufacturer in our EV data), non-Tesla BEVs, and PHEVs. We find that Teslas consume substantially more electricity than the BEVs and PHEVs, though all three types charge more at night than during the day.

Using our preferred difference-in-difference specification, we find that Teslas add 0.236 kWh per hour (SE 0.014, $p < 0.01$) to household consumption, while non-Tesla BEVs and PHEVs increase energy use by almost half this amount: 0.103 kWh per hour (SE 0.008, $p < 0.01$) and 0.090 kWh per hour (SE 0.013, $p < 0.01$), respectively. This is likely to be explained by a combination of factors, including battery capacity and differential household selection into EV types.

III. Discussion

We estimate that the average PG&E EV-owning household uses 2.9 kWh per day charging their vehicle at home. By contrast, California regulators rely on residential charging data reported by the utilities for households with dedicated EV meters. These meters report daily average usage between 6 and 9.8 kWh per day (Joint Utilities 2019), more than twice our estimate. This discrepancy may adversely affect decisions about electricity distribution infrastructure investments as well as lead to biased estimates of EV-related pollution abatement benefits. The implications relating to eVMT are also far reaching.

To translate our estimates into eVMT, we first adjust for nonresidential charging. The California Low-Carbon Fuel Standard (LCFS) program (California Air Resources Board 2020) indicates that between 85 and 90 percent of EV charging occurs at home. This figure is based on numbers that our analysis shows are likely biased; when we account for our lower in-home charging numbers, this suggests that 67 percent of charging occurs at home.[6] We therefore scale our estimates up to obtain a total daily charging estimate. We translate this into eVMT by first assigning all nonresidential charging to BEVs and then combining our Tesla and non-Tesla BEV charging estimates with vehicle-specific miles per kWh from DataOne Software and the overall composition of these vehicles in our sample. We find that average eVMT among PGE BEVs is approximately 6,700 eVMT per year and about 1,700 eVMT per year for PHEVs (which we assume charge only at home). While PHEVs likely drive additional miles on gasoline, overall eVMT is substantially lower than VMT in gasoline-powered cars. This raises questions about (among other things) the true extent of EV usage at present, how EVs fit into the residential transportation portfolio, and the role of gasoline and electricity prices on EV usage.

Future research should seek to test a variety of potential explanations for the apparent low utilization of EVs. First, buyers of EVs to date may not represent the broader vehicle-owning population. Second, the marginal utility of eVMT may be lower than that of travel in conventional vehicles. This may be true for a variety of reasons, including an absence of sufficiently dense charging networks, range anxiety, or other attributes of the EV travel experience. Third, EVs may be complements to gasoline-powered vehicles rather than substitutes for them. The vision of transportation electrification rests on EVs leading to a substitution of VMT away from conventional cars. If, instead, EVs are primarily owned by households with multiple cars, it will be important to understand why. Fourth, low eVMT may be a natural response to high electricity prices in California. While recent evidence suggests this may not be the case (Bushnell, Muehlegger and Rapson 2021), the influence of both electricity and gasoline prices on demand for and usage of EVs remains an area requiring further research. This paper demonstrates how pairing rich data on household-level electricity consumption with vehicle registration information can help answer these and other questions.

[6] Recent LCFS administrative data break out self-reported total nonresidential kWh. There are strong financial incentives to report nonresidential charging to this program, and thus it is reasonable to assume that the vast majority of nonresidential charging is reflected in the LCFS data. Even so, our assumptions allow for substantial unreported charging and imply a greater amount of nonresidential charging per vehicle during 2014–2017 than the LCFS reports for 2019.

REFERENCES

Burlig, Fiona, James Bushnell, David Rapson, and Catherine Wolfram. 2021. “What Drives Electric Vehicle Usage?” Unpublished.

Burlig, Fiona, Christopher Knittel, David Rapson, Mar Reguant, and Catherine Wolfram. 2020. “Machine Learning from Schools about Energy Efficiency.” *Journal of the Association of Environmental and Resource Economists* 7 (6): 1181–1217.

Bushnell, James, Erich Muehlegger, and David Rapson. 2021. *Energy Prices and Electric Vehicle Adoption*. Davis, CA: UC Davis Energy Economics Program.

California Air Resources Board. 2020. "Low Carbon Fuel Standard Quarterly Summary of Data." https://ww3.arb.ca.gov/fuels/lcfs/lrtq-summaries.htm.

California Energy Commission. 2018. California Energy Demand 2018–2030 Revised Forecast.

Davis, Lucas W. 2019. "How Much Are Electric Vehicles Driven?" *Applied Economics Letters* 26 (18): 1497–1502.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates. 2016. "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors." *American Economic Review* 106 (12): 3700–3729.

Joint Utilities. 2019. *7th Joint IOU Electric Vehicle Load Research Report.* Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric.

Tal, Gil, Seshadri Srinivasa Raghavan, Vaishnavi Chaitanya Karanam, Matthew P. Favetti, Katrina May Sutton, Jade Motayo Ogunmayin, Jae Hyun Lee et al. 2020. *Advanced Plug-in Electric Vehicle Travel and Charging Behavior Final Report*. Sacramento: California Air Resources Board.

Low energy: Estimating electric vehicle electricity use

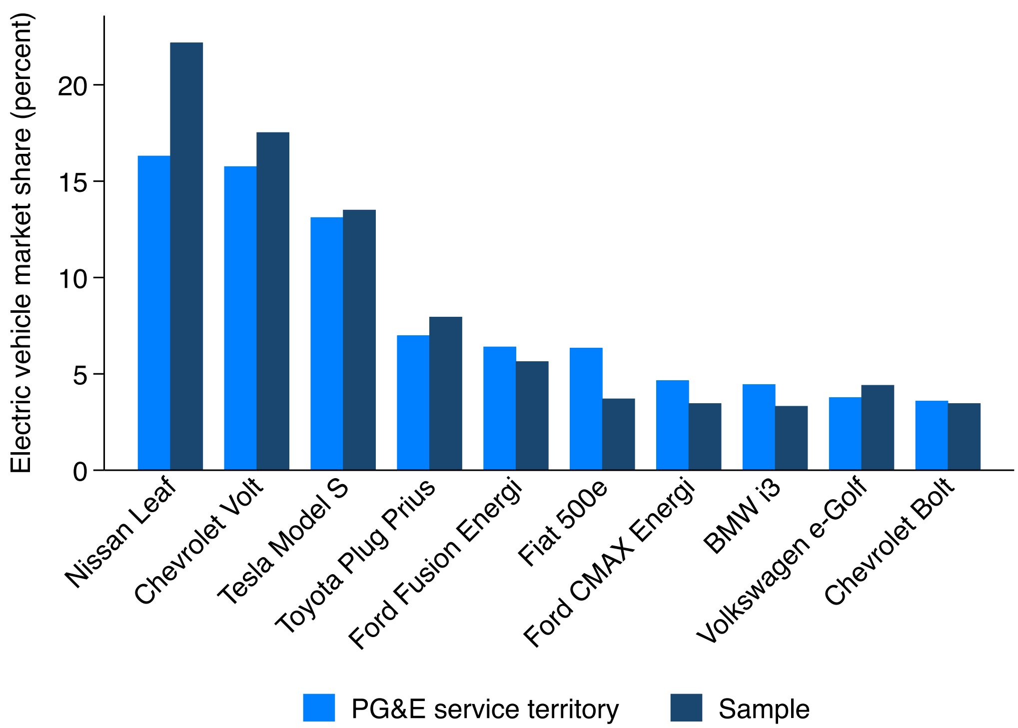
Fiona Burlig, James Bushnell, David Rapson, and Catherine Wolfram

Supplementary Appendix: For online publication

Sample composition of EVs

Figure A1 compares the market shares of EVs in our empirical sample to the overall PG&E population, and demonstrates that our sample has representative coverage of EV models in the utility territory that we study. The sample appears to slightly overweight the most popular cars and slightly underweight less popular cars. This may be an artifact of the sampling frame. As mentioned above, the electricity meter data overweight households in Census Block Groups that have high EV penetration; Figure A1 suggests that these areas may disproportionately own the most popular models.

Figure A1: Composition of EV fleet: Population vs. empirical sample



Notes: This figure presents market shares of the top-ten EV models in the empirical sample and the population of EVs in Pacific Gas & Electric territory from which it was drawn.

Robustness checks

Results presented in the body of the paper are robust to inclusion of control variables. In this Appendix, we present regression counterparts to Figure 1 using various fixed effects. Table A1 shows the average difference-in-differences estimates of the effect on household load resulting from the addition of the average EV in our sample. All columns control for solar installation at the household level. The data are collapsed to the household-by-week-of-sample level.

Table A1: Difference-in-differences: Effect of EV registration on household load

	kWh/hr	kWh/hr	kWh/hr	kWh/hr	kWh/hr	kWh/hr
EV Post	0.339***	0.133***	0.119***	0.123***	0.150***	0.121***
	(0.030)	(0.020)	(0.008)	(0.009)	(0.009)	(0.007)
Solar Post	-0.279***	-0.816***	-0.795***	-0.843***	-0.701***	-0.804***
	(0.024)	(0.036)	(0.025)	(0.030)	(0.028)	(0.025)
HH FEs	No	Yes	No	No	No	No
HHxYear FEs	No	No	Yes	No	Yes	Yes
HHxMofY FEs	No	No	Yes	Yes	No	Yes
Week-of-Sample FEs	No	No	No	Yes	Yes	Yes
Mean Dep. Var	0.77	0.77	0.77	0.77	0.77	0.77
Observations	69,751,085	69,735,740	69,305,961	69,585,082	69,382,114	69,305,961
Within R^2	0.01	0.77	0.91	0.87	0.82	0.91

Moving left to right, specifications include increasingly fine household and time fixed effects. The main conclusion is that controlling for time-invariant household characteristics is important, which can be seen by comparing results in column 1 (which has no fixed effects) and columns 2 through 6. The coefficient on EV arrival is much higher in column 1 due to the fact that households with high baseline electricity usage are more likely to purchase an EV. Coefficient estimates in columns 2 through 6 consistently fall within the range of 0.12-0.15 kilowatt-hours per hour.

Our preferred estimate, 0.12, is in the right-most column. This estimate controls for aggregate patterns in electricity usage by including week-of-sample fixed effects. Household-by-year effects capture factors such as trends in charging station density near each household, and any trends in non-EV electricity usage that may be correlated with the decision to purchase an EV. Household-by-month-of-year fixed effects control for seasonal patterns in electricity demand at the household level, which may confound estimates of the treatment effect if EVs purchases are concentrated in particularly low- or high-electricity usage months.

Table A2 decomposes the difference-in-differences result by car type. Once again, the importance of controlling for household fixed effects is apparent. This table also confirms the main conclusions from Figure 1. Overall, Teslas consume more than twice the amount of electricity via

Table A2: Difference-in-differences: Effect of EV registration on household load, by car type

	kWh/hr	kWh/hr	kWh/hr	kWh/hr	kWh/hr	kWh/hr
Tesla Post	0.542***	0.242***	0.233***	0.223***	0.314***	0.236***
	(0.039)	(0.029)	(0.015)	(0.017)	(0.022)	(0.014)
Non-Tesla BEV Post	0.147***	0.116***	0.106***	0.108***	0.114***	0.103***
	(0.020)	(0.016)	(0.008)	(0.008)	(0.010)	(0.008)
PHEV Post	0.472***	0.104***	0.086***	0.094***	0.119***	0.090***
	(0.055)	(0.023)	(0.013)	(0.012)	(0.011)	(0.013)
Solar Post	-0.281***	-0.817***	-0.796***	-0.844***	-0.702***	-0.804***
	(0.024)	(0.036)	(0.025)	(0.029)	(0.028)	(0.025)
HH FEs	No	Yes	No	No	No	No
HHxYear FEs	No	No	Yes	No	Yes	Yes
HHxMofY FEs	No	No	Yes	Yes	No	Yes
Week-of-Sample FEs	No	No	No	Yes	Yes	Yes
Mean Dep. Var	0.77	0.77	0.77	0.77	0.77	0.77
Observations	69,751,085	69,735,740	69,305,961	69,585,082	69,382,114	69,305,961
Within R^2	0.01	0.77	0.91	0.87	0.82	0.91

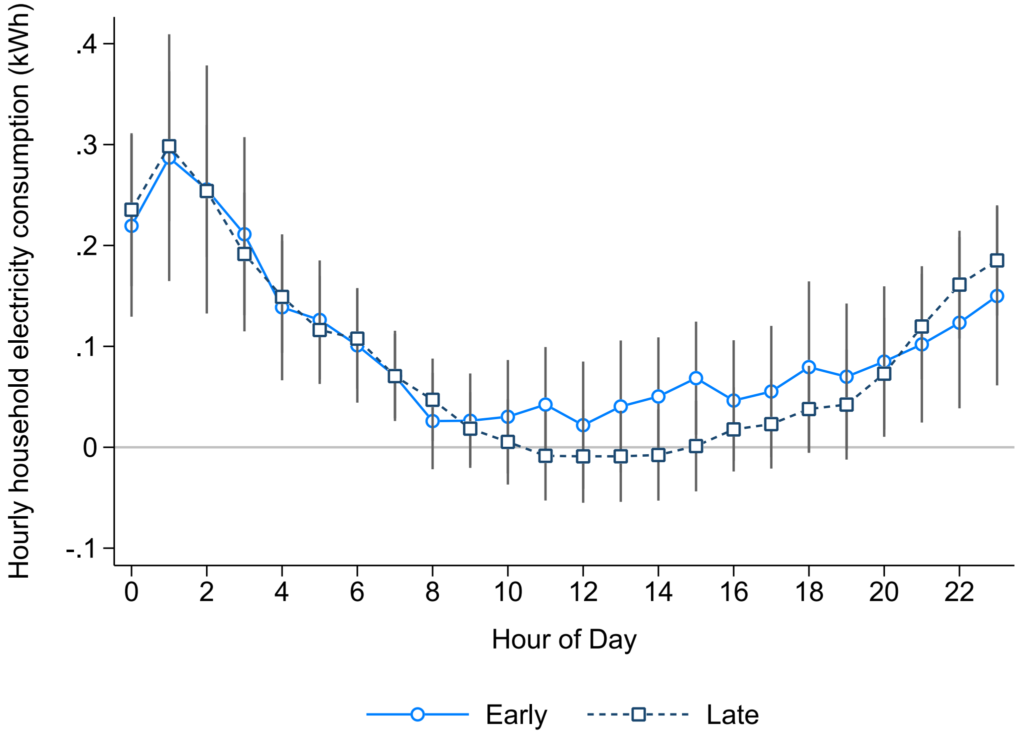
home charging than other BEVs and PHEVs. Moreover, there is little difference in average household charging load between non-Tesla BEVs and PHEVs. Some readers may have expected (as we did) PHEVs to exhibit lower home charging load due to the availability of an internal combustion engine that can run on gasoline. However, these results imply that PHEV owners likely charge their EV battery regularly.

Early vs. late adopters

Figure A2 plots difference-in-differences estimates of the change in household load, by hour-of-day, arising from the addition of an EV. “Early” adopters buy an EV in 2014 and “Late” adopters buy in 2017. Overall, there is little difference in home charging load across these two groups, although late adopters home-charge their EVs slightly less, on average, than early adopters. This is particularly true during the workday.

The implications for eVMT are unclear. If the fraction of overall charging that occurs at home remains constant across years, these results imply that eVMT is slightly decreasing over time. On the other hand, increases in EV battery capacity over the period of study have expanded EV range, and away-from-home charging is unobserved. It is possible that these effect outweigh any decline in home charging. California Air Resources Board (2020) indicates that the share of commercial charging is increasing slowly since 2018, but their published data do not go back far enough to confirm whether this trend was occurring during our sample. More research is needed.

Figure A2: Impacts of EV adoption on household electricity use: Early vs late adopters



Notes: This figure presents our estimates of the impact of EV adoption on household electricity consumption, comparing early (2014) and late adopters (2017). Standard errors are two-way clustered at the Census block group and week-of-sample level.

Appendix References

California Air Resources Board. 2020. *Low Carbon Fuel Standard Quarterly Summary of Data.* Technical report.