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Estimating Residential Electric Vehicle Electricity Use

Authors
Burlig, Fiona, PhD
Bushnell, James, PhD
Rapson, David, PhD
et al.

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RESEARCH REPORT

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Estimating Electric Vehicle Residential Electricity Use

Fiona Burlig, Ph.D., Assistant Professor, Harris School of Public Policy, University of Chicago
James Bushnell, Ph.D., Professor, Department of Economics, University of California, Davis
David Rapson, Ph.D., Professor, Department of Economics, University of California, Davis
Catherine Wolfram, Ph.D., William F. Pounds Professor of Energy Economics, Sloan School of Management, Massachusetts Institute of Technology

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16. Abstract
The widespread adoption of electric vehicles (EV) is a centerpiece of California's strategy to reach net-zero carbon emissions, but it is not fully known how and where EVs are being used, and how and where they are being charged. This report provides the first at-scale estimate of EV home charging. Previous estimates were based on conflicting surveys or extrapolated from a small, unrepresentative sample of households with dedicated EV meters. We combined billions of hourly electricity meter measurements with address-level EV registration records from California households, including roughly 40,000 EV owners. The average EV increases overall household load by 2.9 kilowatt-hours per day, well under half the amount assumed by state regulators. Results imply that EVs travel less than expected on electric power, raising questions about transportation electrification for climate policy.

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Disclaimer

Estimating Electric Vehicle Residential Electricity Use

Fiona Burlig, Ph.D., Assistant Professor, Harris School of Public Policy, University of Chicago
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Executive Summary

Executive Summary

Policymakers attempting to guide transportation electrification lack rigorous estimates of one of the most important pieces of information: how much electricity do electric vehicles (EVs) actually use. This lack exists because of data limitations. The majority of EV charging occurs at home, so it is difficult to distinguish from other uses on the home's electricity meter. Infrastructure planning and the implementation of policies such as EV incentive programs and the Low Carbon Fuel Standard (LCFS) have had to rely on either survey data or heuristic approximations to estimate the amount and timing of electricity use devoted to EVs.

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. Although California has over 1.1 million EVs, only a fraction are charged at home using a meter dedicated to EV use. Through 2022, data from this small sample of households—who have voluntarily invested in home charging and metering infrastructure—have been taken as representative of all EV-owning households in the implementation of policies, such as the LCFS. More recently, these estimates have been supplemented by a larger, but still somewhat selected, sample of charging data self-reported by vehicle manufacturers.

This report presents what we believe to be the first attempt to rigorously and empirically measure the impact of EV adoption on household electricity consumption devoted to electric vehicles. We applied hourly electricity consumption data from 2015 to 2019 for a random sample of 2 percent of the households in California's three major investor-owned utilities (IOUs): Pacific Gas and Electric (PG&E), San Diego Gas & Electric (SDG&E), and Southern California Edison (SCE). We then combined this data with household-level EV registration data to estimate the impact of EVs on residential consumption.

Our main analysis deploys an event study approach in which we pair household-level data on EV adoption with household-level data on electricity consumption to estimate the change in load resulting from EV adoption. This approach enabled us to estimate the relationship between EV adoption and load for the average EV-owning household, something that has been challenging in prior analyses because of the lack of sub-metered data. We compared our estimates of household usage to load at EV-dedicated meters to demonstrate the potential selection bias involved in current estimates of EV load that rely exclusively on directly measured households. Our results indicate that this bias is substantial and significant. We estimated an average daily per-vehicle EV residential charging consumption of 3.6–4.8 kWh during 2015–19. This amount is well below the 7.2–8 kWh used by the small sample of directly metered households on which the award of LCFS credits was based.

We also examined the hourly breakdown, or "load-profile," of EV charging electricity demand. The bulk of EV charging happens in the early morning hours when the California electricity system is not capacity constrained and is also relatively c. We investigated the heterogeneity in charging behavior by vehicle type and by electricity rate class—there is substantial variation across vehicle types, with Tesla owners consuming much more electricity than those of other vehicle makes. Households with plug-in hybrid electric vehicles (PHEV) use considerably less electricity than Tesla-owning households.

Our research also reviewed EV charging behavior in lower-income households that are enrolled in the California Alternate Rates for Energy (CARE) program. These households are proportionately less likely to purchase an EV, and their home charging usage was close to 20 percent lower than non-CARE households. This lower level of charging appears to be largely explained by differences in the type of vehicles purchased (fewer Teslas and more PHEVs).

Our results highlight the need for higher quality data on the amount and location of EV charging. Increasingly, vehicle original-equipment manufacturers (OEM) collect charging data from their vehicles, but these data are only selectively made available to researchers or regulators. Utility planning and state regulation should also consider the differential impacts of PHEVs compared to battery electric vehicles (BEVs). For example, the LCSF awards the same amount of credits for households with registered PHEVs as it does for BEVs, effectively assuming that electricity consumption is the same for all vehicle types. However, the results of this research indicate that BEVs consume substantially more electricity than PHEVs.

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Introduction

Policymakers attempting to guide transportation electrification lack rigorous estimates of one of the most important pieces of information: how much electricity do electric vehicles (EVs) actually use. This lack exists because of data limitations. The majority of EV charging occurs at home, so it is difficult to distinguish from other uses on the home's 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 might have an inaccurate understanding 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 gas-powered vehicle. If EVs are being driven as much as conventional cars, it shows 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 questions about the rate at which the technology will replace trips currently using gasoline. Data on residential EV charging is also important for informing utility planning and investment. While there is a general sense that electrification will require investment in utility distribution systems, the optimal size and location of those investments depends on where and when EVs are likely to be charged. Ideally, policymakers should have a more complete picture about the role EVs play in a region's transportation portfolio because commitments are being made to the technology as one of the key solutions to the decarbonization of transportation.

This report presents 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]. We apply hourly electricity consumption data from 2015 to 2019 for a random sample of 2 percent of the households in California's three major investor-owned utilities (IOUs): Pacific Gas and Electric (PG&E), San Diego Gas & Electric (SDG&E), and Southern California Edison (SCE).[1] The randomness of our sample eliminates the risk of selection or response bias that can influence survey-based approaches. We combined this data with household-level EV registration data to estimate the impact of EVs on residential consumption. We deployed standard event study and difference-in-differences methods to estimate the change in overall household electricity load around EV registration events.

Our estimates indicate that the residential EV charging load in California between 2015 and 2019 was surprisingly low. In our preferred specification, we found that adopting an EV increased household electricity consumption by .154 kilowatt-hours (kWh) per hour, or 3.7 kWh per day during this time span. These estimates are substantially lower than concurrent official residential EV charging estimates used in regulatory proceedings (e.g., see Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric,

[1]This random sample is complemented by a larger, purpose-built sample of roughly 10 percent of households across these three utilities which yielded quantitatively very similar results.

2019). The discrepancy between the estimates likely results from selection bias in the official estimates, which are extrapolated from a small number of households that have installed dedicated EV meters.

Policy and Regulatory Context 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 are affected by transportation electrification. The profile of residential load is already changing rapidly due to investments in behind-the-meter solar generation, and EV charging might further alter the residential load profile. The timing of EV-related electricity demand affects both the economic value of the energy consumed and marginal emissions. Further, the price responsiveness of EV load 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.

To date, the largest challenge in evaluating the economic and environmental impact of EVs has been the lack of quality data about their energy demand and vehicle utilization. Without such data at scale, researchers and policymakers have been forced to rely on survey or measurement data from small, selected samples,[2] and the resulting estimates vary widely. Using data from the 2017 National Household Travel Survey [Davis, 2019], pure battery EVs are driven less than two-thirds of the miles of conventional cars and less than half the miles of conventional hybrids. However, a survey by the UC Davis PHEV Center finds almost double the electric vehicle miles traveled (eVMT) of those cited by Davis [PHEV Center, 2020].

As an alternative to using survey data for estimating eVMT, another method 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 [Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric, 2019]. While charging at networks operated either by commercial charging businesses or vehicle manufacturers such as Tesla is directly metered, the California Air Resources Board (CARB) estimates that 85 percent of EV charging occurs at home [California Air Resources Board, 2020]. Thus, the vast majority of EV charging is measured only by the vehicle manufacturers who treat this information as proprietary and confidential. To form projections of future electricity use, California state agencies use measurements from the small share of EVs that are directly metered. Of course, if charging via these meters is not representative, this can paint an inaccurate picture of home EV charging. For example, households that install EV-specific meters might be wealthier, buy cars with bigger batteries, or be more inclined to use their cars.

We assembled household-level data from two main sources: electricity meter data from a 2 percent random sample of PG&E's residential customers, and EV registration data from the California Department of Motor

[2]The best data on EV charging use is likely within the vehicles themselves. Most OEMs collect charging data from the cars that they have sold, but this data is held closely due to strategic business interests and privacy concerns.

Vehicles (DMV). For robustness, we also obtained a much larger sample of all residential meters in selected zip codes or census block groups. The results from these larger samples are quite similar to those reported here. For more details on these data, see Burlig et al. (2021).

Electricity Meter Data

We obtained three types of data from the three major California investor-owned utilities: monthly billing information, hourly electricity consumption data, and customer details. In addition to the consumption and billing data, we observed each customer's street address, latitude and longitude, rate class, and a solar panel interconnection date where applicable. The sample consists of 581,983 households and over 1.5 billion hourly electricity consumption observations. Table 1 summarizes statistics for these households.

We observed that EV households are much more likely to have solar and consume more electricity per hour. They also have higher bill consumption and bill amounts than their non-EV-owning counterparts. Non-EV owning households are more likely to be on the means-tested CARE rate and less likely to be enrolled in a time-varying electricity rate.

Table 1. Sample Summary Statistics

	Non-EV Households		EV Households		All Households	
	Mean	SD	Mean	SD	Mean	SD
Elect. Consumption (kWh/h)	0.648	0.572	0.806	0.685	0.651	0.575
CARE	0.203	0.402	0.168	0.374	0.202	0.402
Standard Rate	0.944	0.230	0.696	0.460	0.940	0.237
TOU Rate	0.062	0.241	0.274	0.446	0.065	0.246
EV Rate	0.002	0.045	0.135	0.342	0.004	0.062
PGE Share	29.5%		36.2%		29.6%	
SCE Share	59.8%		55.7%		59.8%	
SDGE Share	10.7%		8.1%		10.7%	
Total EV	0		9,415		9,415	
Total Tesla	0		2,746		2,746	
Total BEV	0		2,313		2,313	
Total PHEV	0		4,356		4,356	
Total ICE	362,755		9,376		372,131	
Total Households	581,983		8,089		590,072	

Notes: This table presents summary statistics for the Representative Sample (RES). Figures for EV households and non-EV households are presented separately, in addition to those for the entire RES. ICE count denotes the mean number of ICE vehicles per household. Elect. Consumption denotes the mean hourly electricity consumption, by household-week (in kWh/h). Rate variables denote the proportion of households on the specific type of rate schedule.

EV Registration Data

We obtained California DMV registration records for 2008 to 2019. Our dataset contains the universe of EVs registered in the state during this time period. For each EV, we observed 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 to track the vehicles over time. We observe 750,073 unique vehicles, of which 38,173 are in ZIP codes belonging to the sample of the PG&E service territory that matches our analysis sample, and 55,503 of these are in a California IOU service territory between 2015 and 2019, the time period of our electricity use information.

Cleaning and Matching the Data

We used a string matching algorithm to assign EVs to our sample households. We cleaned the data so that common words are represented in the same way in both datasets (e.g. “ave” vs. “avenue” and “st” vs. “street”). Then we used a string matching algorithm to assign EVs to the sample households. We performed an exact match on address and then used a fuzzy string match to finalize the merge, resulting in matching 9,055 EVs with households in our sample.[3] Figure 1 summarizes the top-10 models in our sample compared to the overall registration share during this same time period. The two samples broadly match, although our sample does feature slightly more Toyota Prius plug-in vehicles and slightly less Tesla S and X class vehicles.

[3]The larger sample contains every household in a selection of ZIP codes in the PG&E territory. Using the same matching method, we determined that 90 percent of the EVs in these ZIP codes were successfully matched to a specific household in our utility data.

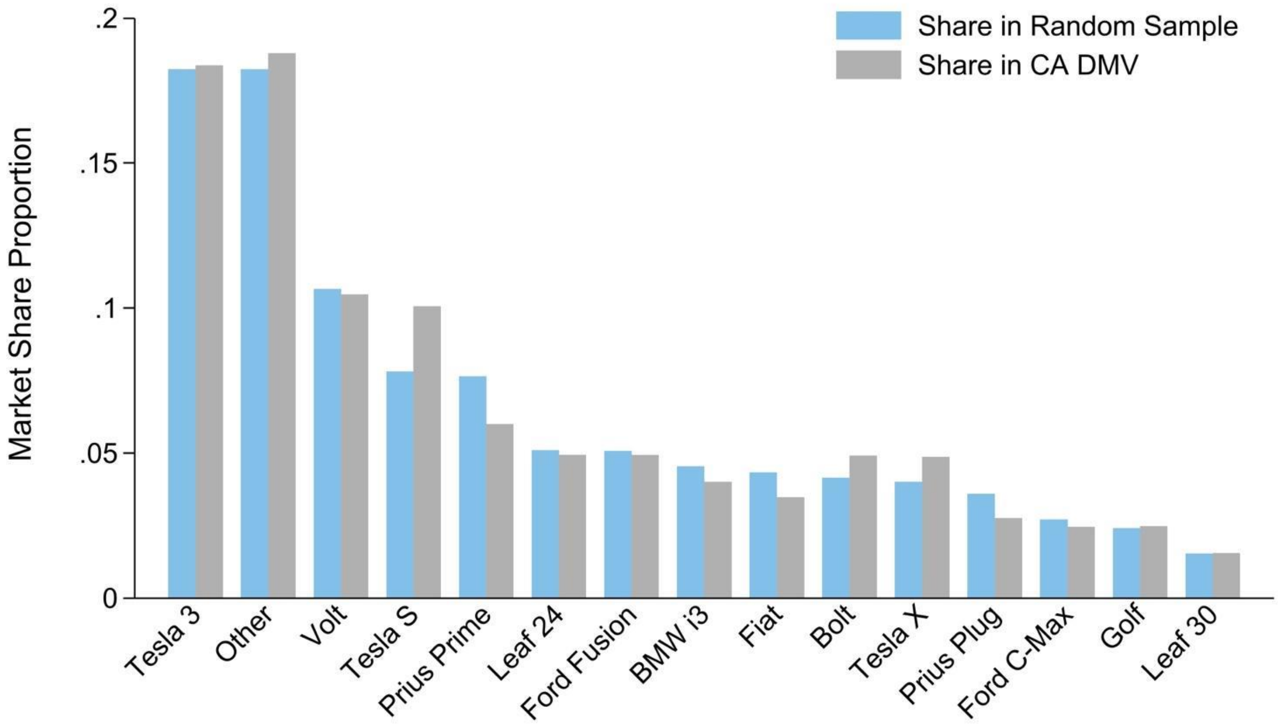

Figure 1. EV Shares by Model

Empirical Design and Results

With access to this unique dataset on both electricity use and EV registration, we empirically estimated the effects of EV ownership on residential energy use among this large random sample of California households.

To quantify EV usage, we estimated 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:

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

- where Y_{ith} is electricity consumption (measured in kWh per hour) in household *i* during week-of-sample *t* in hour-of-day *h*.[4]
- EV_{it} is a count of the number of EVs registered to household *i* in week *t*, and is equal to 0 for households without EVs.
- $Solar_{it}$ is an indicator equal to 1 if household *i* has installed solar panels by week *t; otherwise it is* 0, 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 the results toward 0 because installing solar reduces net electricity demand.[5]
- α_i represents household-by-year and household-by-month-of-year fixed effects.
- δ_t are week-of-sample fixed effects. Our results are robust to using more parsimonious fixed effects, including using only household fixed effects (see Burlig et al. 2021 for additional robustness).
- ε_{ith} is an error term, which we two-way cluster at the Census Block Group and week-of-sample levels. We presented two extensions to this main specification: an event study approach in which we estimated separate beta and gamma 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 that estimates separate beta and gamma coefficients for each hour of the day. We also explored heterogeneity by EV type: Tesla, PHEVs (PHEVs), and non-Tesla BEVs.

[4]We collapsed the data to the household *x* week-of-sample *x* 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).

[5]One concern in this setting is measurement error in the treatment dates. If the DMV registration records or PG&E solar installation are misaligned with actual adoption, the 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.

Identification

For this approach to capture the causal effect of EV adoption on household electricity use, we required that households that adopted EVs would have remained on a similar counterfactual trend to non-adopting households 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. In the left panel of Figure 1, prior to EV adoption, there is a flat pre-trend. And, as shown in Figure 2, our treatment effects are concentrated in the evening hours, consistent with survey evidence about EV charging patterns (Davis, 2019). 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.

Results

We found that adopting an EV increases a household's electricity consumption by 0.154 kWh per hour (s.e. 0.007, $p < 0.01$), or approximately 3.7 kWh per day. Figure 2 presents this result in the form of an event study.[6] This figure has several notable features. First, prior to EV adoption, the energy use pre-trend is quite flat, providing support in favor of our identifying assumption. Second, there is a sharp increase in household use when a household adds an EV. Finally, we see that our treatment effect is stable up to 25 weeks after EV adoption.

[6] In this event study, we set $t = 0$ as the DMV registration date, which is about 4–5 weeks after the vehicle's arrival at a household 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 2 reflects the 4–5 week difference.

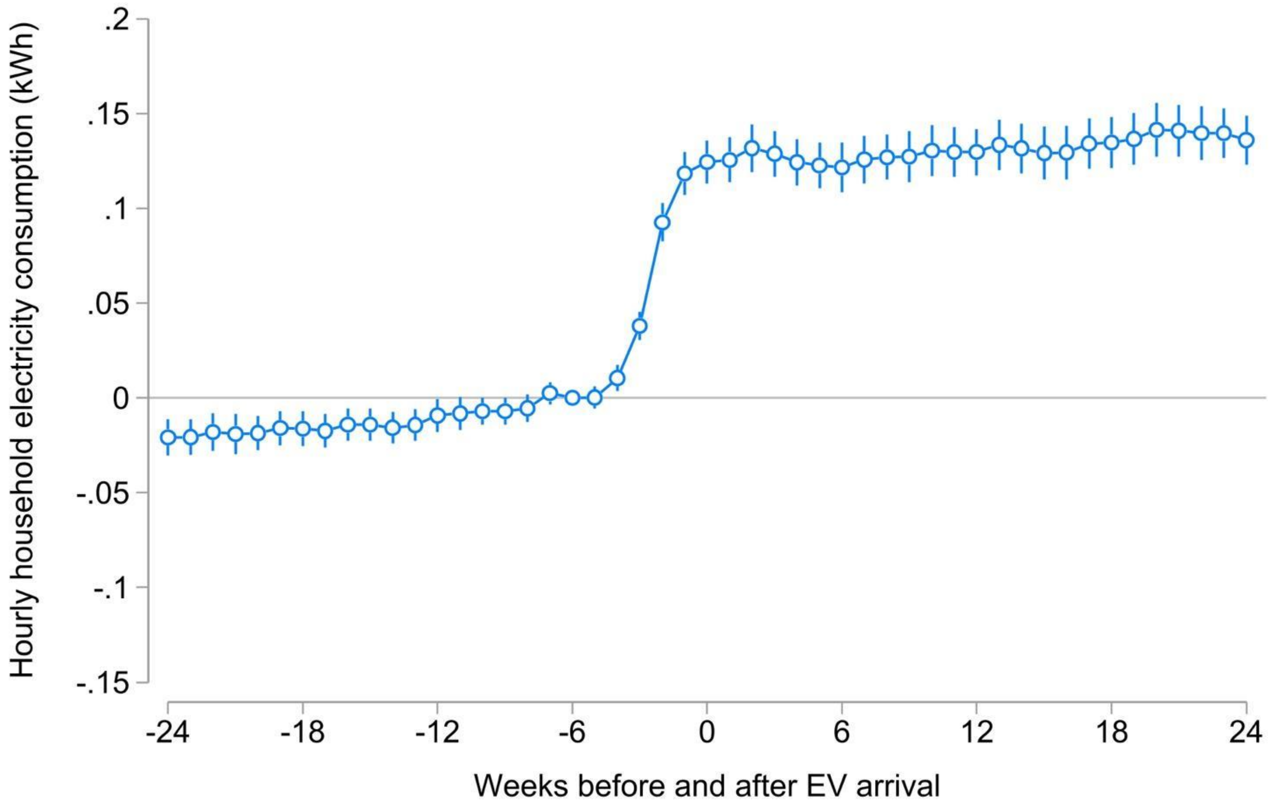

Figure 2. Impacts of EV Adoption on Household Electricity Use

Note: Error bars reflect 95 percent confidence intervals. Standard errors are two-way clustered at the Census block group and week-of-sample level.

Table 2 presents the results of several specifications of the above difference-in-difference regression for the random sample. These results are essentially regression counterparts to Figure 1 using various fixed effects. All columns control for solar installation at the household level. The data is collapsed to the household-by-week-of-sample level.

Moving from left to right, the 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 the results in columns 1 and 2 (which have no fixed effects) to columns 3 through 5. The coefficient on EV arrival count is much higher in columns 1 and 2, probably due to the fact that households with high baseline electricity usage are more likely to purchase an EV. Coefficient estimates in columns 3 through 5 consistently fall within the range of 0.154 to 0.156 kWh per hour.

Table 2. Difference-in-Differences Effect of EV Registration on Household Load

A. Pooled	(1)	(2)	(3)	(4)	(5)
EV count	0.251***	0.255***	0.154***	0.156***	0.154***
	(0.012)	(0.012)	(0.009)	(0.006)	(0.005)
Solar	-0.270***	-0.267***	-0.750***	-0.744***	-0.759***
	(0.019)	(0.018)	(0.034)	(0.027)	(0.026)
Household	No	No	Yes	Yes	No
Week-of-sample	No	Yes	No	Yes	Yes
Household × MofY	No	No	No	No	Yes
EV Arrivals	9,387	9,387	9,387	9,387	9,387
EV Departures	2,248	2,248	2,248	2,248	2,248
Unique EVs	9,415	9,415	9,415	9,415	9,415
Mean Dep. Var	0.65	0.65	0.65	0.65	0.65
Observations	73,602,564	73,602,564	73,587,194	73,587,194	73,508,457

Notes: This table presents estimates of the effect of a change in the number of electric vehicles at a household on hourly household electricity consumption. Solar is a time-varying indicator equal to 1 if the household has solar. To account for measurement error around EV arrival/departures, we drop donuts of -4 to +4 weeks around arrival dates and -10 to +20 weeks around departure dates. The data are restricted to a 52-week window around arrival/departure events. Standard errors are two-way clustered by census block group and week-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Our preferred estimate, 0.154 kWh, is in the right-most column. This estimate controls for aggregate patterns in electricity usage by including week-of-sample fixed effects. Household-by-month-of-year fixed effects control for seasonal patterns in electricity demand at the household level, which can confound estimates of the treatment effect if EVs purchases are concentrated in particularly low- or high-electricity usage months.

Heterogeneity by Vehicle Type

Next, we present heterogeneous effects along two dimensions. Figure 3 shows the effect of EV adoption on household electricity use for each hour of the day by vehicle type.

The EV treatment effects are concentrated between 10 p.m. and 6 a.m., which is consistent with households charging their EVs when they come home and leaving them plugged in overnight. This hourly pattern has environmental implications because 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.

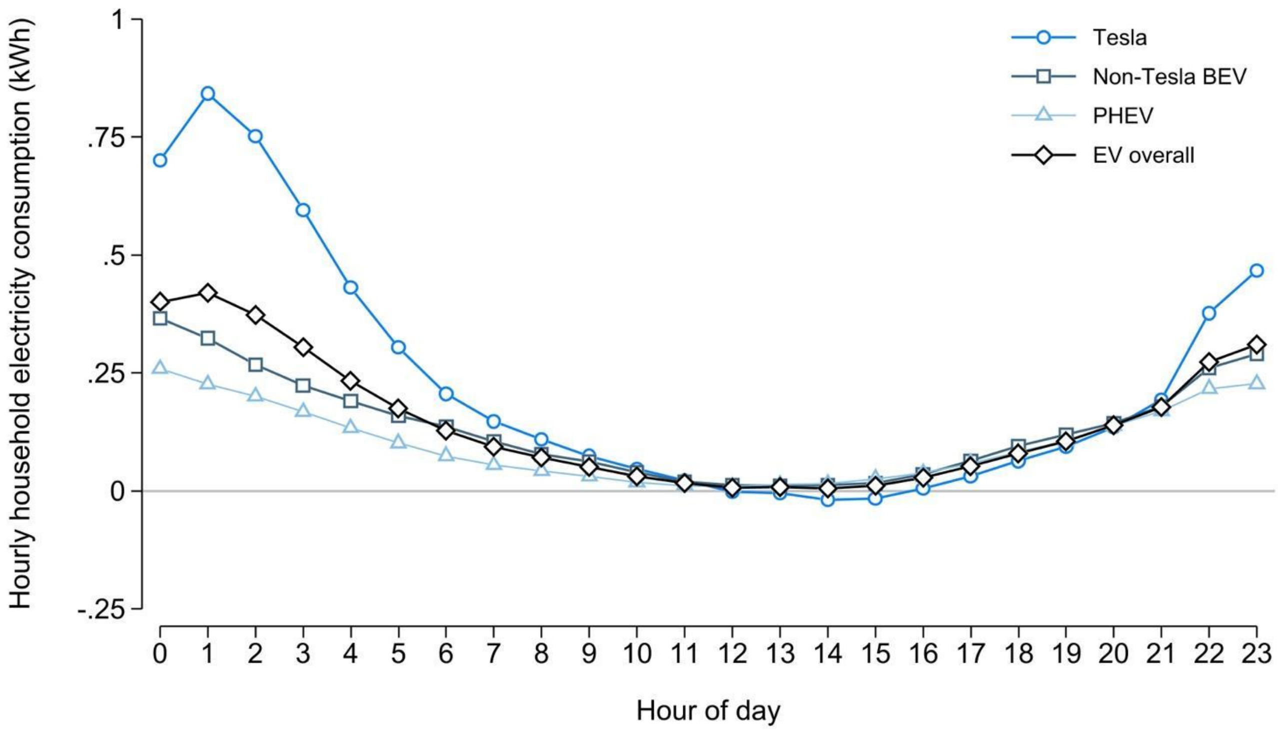

Figure 3. Hourly Change in Household Electricity Use

Note: This figure plots difference-in-difference estimates by hour of day and vehicle type. We plotted separate estimates for Teslas, non-Tesla BEVs, and PHEVs, as well as an overall estimate using all EVs.

Figure 3 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, although all three types charge more at night than during the day.

We applied the same analysis described to subsamples of the datasets divided into households located in the service territories of PG&E, SDG&E, and SCE. The results for our preferred specification (Table 2, column 5) are presented under Model A in Table 3. Across the three utilities, residential EV charging was the highest in the SCE territory (4 kWh per day) and 20 percent higher than charging in the SDG&E territory. These results appear to be heavily influenced by the charging of Teslas.

Table 3. Difference-in-Difference Estimates by Utility and Vehicle Type

A. Pooled	All	PGE	SCE	SDGE
EV count	0.155***	0.150***	0.167***	0.140***
	(0.006)	(0.007)	(0.008)	(0.018)
Solar	-0.761***	-0.836***	-0.912***	-0.547***
	(0.026)	(0.026)	(0.032)	(0.045)
B. By type	All	PGE	SCE	SDGE
Tesla count	0.261***	0.230***	0.308***	0.182***
	(0.011)	(0.013)	(0.014)	(0.048)
BEV count	0.136***	0.131***	0.143***	0.150***
	(0.008)	(0.012)	(0.010)	(0.021)
PHEV count	0.098***	0.097***	0.103***	0.101***
	(0.006)	(0.009)	(0.007)	(0.026)
Solar	-0.762***	-0.837***	-0.913***	-0.547***
	(0.026)	(0.026)	(0.032)	(0.045)
Household	No	No	No	No
Week-of-sample	Yes	Yes	Yes	Yes
Household × MofY	Yes	Yes	Yes	Yes
EV Arrivals	9,182	3,371	5,088	723
EV Departures	2,321	1,146	947	228
Unique EVs	9,225	3,407	5,064	746
Mean Dep. Var	0.65	0.65	0.67	0.54
Observations	74,333,885	24,853,653	41,163,049	8,317,180

Notes: This table presents estimates of the effect of a change in the number of electric vehicles at a household on hourly household electricity consumption, across different utilities. Panel A presents pooled effects; Panel B presents effects by vehicle type (Tesla/BEV/PHEV). Solar is a time-varying indicator equal to 1 if the household has solar. To account for measurement error around EV arrival/departures, we drop donuts of -4 to +4 weeks around arrival dates and -10 to +20 weeks around departure dates. Standard errors are two-way clustered by census block group and week-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

The lower panel (Model B) of Table 3 reports the same regression with the EV effect broken out by model type. Using a preferred difference-in-difference specification, we find that Teslas add 0.18 to .31 kWh per hour to household consumption, while non-Tesla BEVs and PHEVs increase energy use by almost half this amount: 0.13 to .15 kWh per hour and 0.10 kWh per hour, respectively. This difference is likely to be explained by a combination of factors, including battery capacity and differential household selection into EV types.

In Table 4, we decomposed our results according to the year in which the vehicle was purchased. This table illustrates that residential charging per vehicle increased steadily from 2014 to 2019, almost doubling from 2014 levels. It is important to note that our overall estimate of 0.154 kWh/hour is only marginally less than our 2018 and 2019 values because over two-thirds of the EVs in our sample were registered in these latter years. These annual trends are consistent with the fact that Teslas comprised a much larger share of new vehicles in later years and that households registering Teslas increased their residential consumption by much more than those registering other EVs (Table 4). In other words, the trend of increasing residential EV charging is likely due to a change in the composition of the EV fleet over time rather than a dramatic increase in EV charging within an EV vehicle type.

Table 4. Effects of EV Registration on EV Charging by Year of Registration

	All	2015	2016	2017	2018	2019
EV count	0.154***	0.089***	0.110***	0.123***	0.158***	0.162***
	(0.005)	(0.013)	(0.009)	(0.009)	(0.008)	(0.010)
Solar	-0.759***	-0.758***	-0.758***	-0.758***	-0.759***	-0.759***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Household	No	No	No	No	No	No
Week-of-sample	Yes	Yes	Yes	Yes	Yes	Yes
Household × MofY	Yes	Yes	Yes	Yes	Yes	Yes
EV Arrivals	9,387	1,563	1,916	2,267	3,339	3,329
EV Departures	2,248	1,018	1,072	981	1,045	942
Unique EVs	9,415	1,720	2,144	2,504	3,615	3,615
Mean Dep. Var	0.65	0.65	0.65	0.65	0.65	0.65
Observations	73,508,457	72,868,326	72,918,356	72,944,732	73,019,250	72,974,796

Notes: This table presents estimates of the effect of a change in the number of electric vehicles at a household on hourly household electricity consumption. Effects are estimated for all households as well as for households grouped by year of purchase of EV, from 2015-2019. Solar is a time-varying indicator equal to 1 if the household has solar. To account for measurement error around EV arrival/departures, we drop donuts of -4 to +4 weeks around arrival dates and -10 to +20 weeks around departure dates. The data are restricted to a 52-week window around arrival/departure events. Standard errors are two-way clustered by census block group and week-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Results for Low-Income Customers

We did not directly observe the income or any other demographic information about individual households. However, we did observe whether a household is on a CARE electricity rate. The CARE program offers a 30–35 percent discount on electricity prices for households with income at or below 200 percent of the federal poverty level, adjusted for the number of people in the household. The CARE customers therefore represent one measure of the lower-income cohort of our sample. In our sample, roughly 20 percent of all households and 16 percent of EV purchasing households are on CARE rates (Table 1).

We again estimated our main specification from equation (1) with an additional term capturing the interaction of a change in the number of EVs with CARE status. Estimated usage at CARE households is the sum of the EV count coefficient and the interaction term. This analysis is summarized in Table 5. Overall, CARE households charged their EVs at home roughly 0.30 kWh/hour, or 20 percent less than non-CARE households. The difference was stronger and more significant in the PG&E and SCE territories and not significant in SDG&E territory where our sample is smaller.

Table 5. Residential EV Charging at CARE Households

	All	PGE	SCE	SDGE
EV count	0.160***	0.153***	0.179***	0.133***
	(0.006)	(0.008)	(0.008)	(0.020)
CARE × EV count	-0.028***	-0.051**	-0.045***	0.071
	(0.010)	(0.022)	(0.011)	(0.061)
Solar	-0.761***	-0.836***	-0.913***	-0.547***
	(0.026)	(0.026)	(0.032)	(0.045)
Household	No	No	No	No
Week-of-sample	Yes	Yes	Yes	Yes
Household × MofY	Yes	Yes	Yes	Yes
EV Arrivals	9,182	3,371	5,088	723
EV Departures	2,321	1,146	947	228
Unique EVs	9,225	3,407	5,064	746
Mean Dep. Var	0.65	0.65	0.67	0.54
Observations	74,333,885	24,853,653	41,163,049	8,317,180

Notes: This table presents estimates of the effect of a change in the number of electric vehicles at a household on hourly household electricity consumption, across different utilities, for CARE and non-CARE households. CARE is an indicator that equals 1 if the household was ever on CARE. Solar is a time-varying indicator equal to 1 if the household has solar. To account for measurement error around EV arrival/departures, we drop donuts of -4 to +4 weeks around arrival dates and -10 to +20 weeks around departure dates. Standard errors are two-way clustered by census block group and week-of-sample. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Conclusions

We estimate that the average California EV-owning household used 3.7 kWh per day charging their vehicle at home between 2014 and 2019, with substantial variation across utility service territories and vehicle types. By contrast, during this period California regulators relied 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 (Pacific Gas and Electric, Southern California Edison, and San Diego Gas and Electric, 2019), more than twice our estimate. Such discrepancies can adversely affect decisions about electricity distribution infrastructure investments, as well as lead to biased estimates of EV-related pollution abatement benefits.

For example, California's Low Carbon Fuel Standard (LCFS) applies the estimates of residential charging taken from the small sample of dedicated meters to all EV-owning households in California when it determines the quantity of LCFS credits to award to electricity distributors. In effect, the LCFS assumes that the small sample of households with dedicated meters is representative of all EV-owning households. Our research indicates that this assumption grossly overstated residential EV charging during the period between 2015 and 2019, as shown in Figure 4.

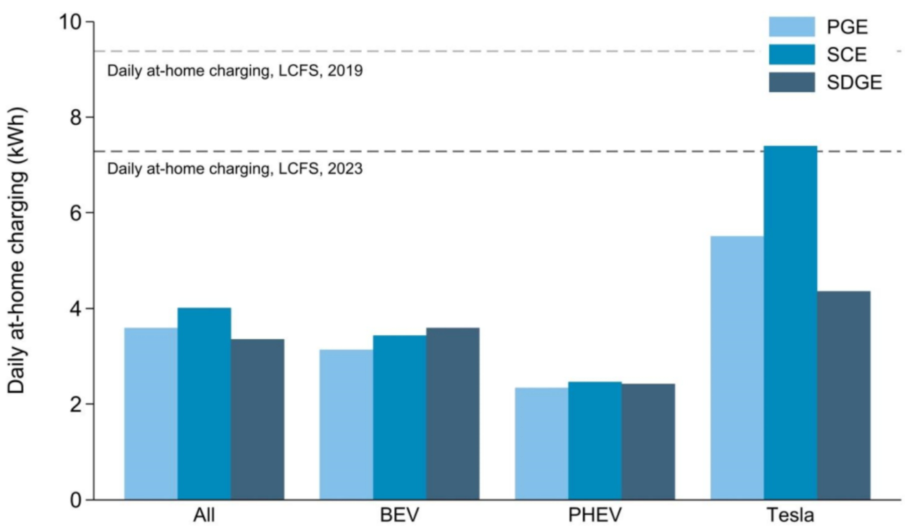

Figure 4. Residential EV Charging Load by Vehicle Type and Utility Service Territory

Note: The bar heights reflect the coefficient estimates reported in Table 3.

The dashed line in Figure 4 represents the average daily charging load of the directly metered households on which estimates of LCFS credits are based in 2019. The bars indicate the charging load from the households in our sample, broken out by vehicle type and utility service territory. Two conclusions emerge. First, the residential charging load was overestimated, at least through 2019, when based upon directly metered households as in the LCFS. Second, the assumption that all EV-owning households use the same amount of electricity regardless of vehicle type or model is also problematic. For example, Tesla households in the SCE territory use close to four times the electricity that PHEV-owning households use, yet both sets of households generate the same amount of LCFS credits under the current assumptions applied by the LCFS program.

Starting in 2023, CARB has updated its methods for calculating residential EV charging to rely on a large amount of self-reported charging data taken from vehicle telematics. Eligible entities can earn "incremental" LCFS credits for EV charging by providing evidence of charging combined with procurement of low-carbon electricity. Charging data from roughly 60 percent of EVs is now reported to CARB through this program. These changes have reduced the average statewide average charging rate used for the LCFS by over 25 percent relative to 2019 levels, moving the official residential charging numbers in the direction of our estimates.

While the currently utilized estimates in the LCFS based on a large amount of telematics data are more accurate and less selective than those based on directly metered households, those estimates (roughly 7.3 kWh per day in 2023) are still higher than ours for residential charging (roughly 4 kWh per day from 2014 to 2019). We hypothesize several reasons for these differences.

First, while the LCFS telematics sample is quite large, now covering over 60 percent of EVs in the state, it is still a somewhat selective sample. To the extent that the CARB sample contains a higher share of high-usage vehicles (e.g., Teslas) with lower to no representation of lower-usage vehicles (e.g., Leafs), our estimates differ based on relative shares of different EV types. Second, per EV charging in 2023, the first year for which CARB telematics data are reported, could be higher than it was in 2019. A third difference might offer interesting insight into the geographic distribution of EV charging demand in the state. Our method estimates EV charging load at residential meters, but the CARB method actually calculates total EV charging net of charging at commercial charging locations specifically registered with the CARB. Thus, the CARB values contain some amount of charging load located at neither registered commercial charging locations nor residences.

There has been recent controversy over the fact that there is no comprehensive registry of non-residential charging locations, nor is there comprehensive data collected on charging station availability. To the extent that the differences between our estimates and CARB's current values reveal a substantial amount of "mystery" charging locations. Further investigation of these values can help guide planning for electricity distribution and increase understanding of current and future EV charging options.

While we do not directly estimate the total miles traveled by EVs in California, we can make some projections based on our results. To translate our estimates into eVMT, we need to first adjust for away-from-home charging. The California LCFS program (California Air Resources Board, 2020) indicates that between 85–90 percent of EV charging was residential in 2019. However, as discussed earlier, this figure is based on residential charging levels that our analysis shows are likely upward biased. More recent LCFS data that uses telematics data rather than dedicated EV meters reports that residential charging is roughly 75 percent of total light-duty vehicle (LDV) charging. Following these more recent data, we assume that 75 percent of BEV charging and 100 percent of PHEV charging occurred at home during our sample, indicating that away-from-home charging accounts for 25 percent of BEV electricity consumption. Using this assumption, we scale our estimates up to obtain a total daily charging estimate.

We translated this into eVMT by first assigning all non-residential 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. Under these assumptions, we found that average eVMT among PG&E BEVs is approximately 6,700 eVMT per year and about 1,700 eVMT for PHEVs (which we assume only charge 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.

Summary

The widespread adoption of zero-emission vehicles (ZEV) is a centerpiece of California's strategy to reach net-zero carbon emissions. But even after a decade of rapidly expanding markets for ZEVs, however, there continue to be important gaps in knowledge about how and where ZEVs are being used, and how and where they are being charged. While electric utilities, state agencies, and vehicle manufacturers possess valuable data that can provide answers to these questions, those institutions rarely share the data with researchers or even each other. In the absence of robust, unbiased empirical data, much research and policy in the ZEV area has had to rely on survey-based or self-reported data that can be heavily influenced by selective responses and technical limitations.

This report presents the results of a multiyear effort to collect and apply the various pieces of data necessary to answer how much electricity is being used for ZEV charging in California homes. We combined high-frequency residential meter data from a fully random sample of California homes with vehicle registration data in a way that allows us to estimate the change in home electricity consumption that coincides with a change in the number of ZEVs registered at a residence.

Between 2015 and 2019, residential electricity consumption increased on average about 3.6 kWh per day upon the arrival of a ZEV at a residence. This average masks the substantial variation across homes and ZEV types. Electricity usage increased only a modest amount in homes registering a plug-in hybrid, while homes registering a Tesla increased consumption by roughly 6.2 kWh per day. Consumption increased about 20 percent less at households enrolled in California's low-income electricity (CARE) rates than in households not enrolled in these rates. Most of this difference can be attributed to the types of ZEVs typically registered at CARE households where, for example, Teslas were less common.

Our residential electricity usage estimates are considerably lower than the figures used for calculating credits for residential electricity charging in California's Low Carbon Fuel Standard (LCFS) program through 2019. Starting in 2023, the LCFS program adopted new methods for calculating residential charging, and the recent figures are closer to our estimates, but still considerably higher. We hypothesize that the remaining difference is due at least in part to the fact that the new LCFS method actually reports charging in locations that are not registered commercial charging locations rather than reporting charging that is explicitly measured as happening at a residence, as we estimated. This difference indicates that there could be substantial charging activity going on in locations that are neither at the home nor at a registered commercial charging site.

The ZEV landscape continues to change quickly. During the period of our sample, through 2019, the common assumption had been that vehicles with ever-larger battery capacities would continue to be introduced and adopted. Indeed, the market saw a large number of SUV, cross-over, and pickup truck BEV models introduced over the past several years. However, the assumptions that drove these trends are now coming under scrutiny amid retrenchment in the BEV market, particularly among larger original equipment manufacturers. In this

evolving policy landscape, impartial information about the location and amount of energy consumed by ZEVs is a critical input for designing ZEV policies and the infrastructure to serve them. This paper demonstrates how pairing rich data on household-level electricity consumption with vehicle registration information can help answer these and other questions.

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