Title

Supercharged? Electricity Demand and the Electrification of Transportation in California

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Publication Date

2020-03-01

DOI

10.7922/G29C6VN1

Supercharged? Electricity Demand and the Electrification of Transportation in California

A Research Report from the University of California Institute of Transportation Studies

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March 2020

REPORT No.: UC-ITS-2019-01 | DOI:10.7922/G29C6VN1

Technical Report Documentation Page

1. Report No. UC-ITS-2019-01	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A

4. Title and Subtitle Supercharged? Electricity Demand and the Electrification of Transportation in California	**5. Report Date** March 2020 **6. Performing Organization Code** ITS-Davis
7. Author(s) Fiona Burlig, Ph.D. James Bushnell, Ph.D., https://orcid.org/0000-0002-8681-9257 David Rapson, Ph.D., https://orcid.org/0000-0001-8711-7030 Catherine Wolfram, Ph.D., https://orcid.org/0000-0001-7327-8626	**8. Performing Organization Report No.** UCD-ITS-RR-20-14
9. Performing Organization Name and Address Institute of Transportation Studies University of California, Davis 1605 Tilia Street Davis, CA 95616	**10. Work Unit No.** N/A **11. Contract or Grant No.** UC-ITS-2019-01
12. Sponsoring Agency Name and Address The University of California Institute of Transportation Studies www.ucits.org	**13. Type of Report and Period Covered** Final Report (October 2018 – September 2019) **14. Sponsoring Agency Code** UC ITS

15. Supplementary Notes
DOI:10.7922/G29C6VN1

16. Abstract
The rapid electrification of the transportation fleet in California raises important questions about the reliability, cost, and environmental implications for the electric grid. A crucial first element to understanding these implications is an accurate picture of the extent and timing of residential electricity use devoted to EVs. Although California is now home to over 650,000 electric vehicles (EVs), less than 5% of these vehicles are charged at home using a meter dedicated to EV use. This means that state policy has had to rely upon very incomplete data on residential charging use. This report summarizes the first phase of a project combining household electricity data and information on the adoption of electric vehicles over the span of four years. We propose a series of approaches for measuring the effects of EV adoption on electricity load in California. First, we measure load from the small subset of households that do have an EV-dedicated meter. Second, we estimate how consumption changes when households go from a standard residential electricity tariff to an EV-specific tariff. Finally, we suggest an approach for estimating the effect of EV ownership on electricity consumption in the average EV-owning household. We implement this approach using aggregated data, but future work should use household-level data to more effectively distinguish signal from noise in this analysis. Preliminary results show that households on EV-dedicated meters are using 0.35 kWh per hour from Pacific Gas and Electric (PGE); 0.38 kWh per hour from Southern California Edison; and 0.28 kWh per hour from San Diego Gas and Electric on EV charging. Households switching to EV rates without dedicated meters are using less electricity for EV charging: 0.30 kWh per hour in PGE. Our household approach applied to aggregated data is too noisy to be informative. These estimates should be viewed as evidence that more focused analysis with more detailed data would be of high value and likely necessary to produce rigorous analysis of the role EVs are playing in residential electricity consumption.

17. Key Words Electric vehicles, plug-in hybrid vehicles, energy consumption, demand, household, residential areas, policy analysis, empirical methods, data analysis	**18. Distribution Statement** No restrictions.

19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 31	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Acknowledgements

This study was made possible through funding received by the University of California Institute of Transportation Studies from the State of California via the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1). The authors would like to thank the State of California for its support of university-based research, and especially for the funding received for this project.

Supercharged? Electricity Demand and the Electrification of Transportation in California

UNIVERSITY OF CALIFORNIA INSTITUTE OF TRANSPORTATION STUDIES

March 2020

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Executive Summary

With California Senate Bills 32 and 100, the state has committed to aggressive new greenhouse gas (GHG) reductions through a strategy focusing on the electrification of the residential, industrial, commercial, and, most significantly, transportation sectors. In particular, the state has devoted substantial financial resources to a broad suite of policies aimed at electrifying passenger transportation.

A variety of California state policies have provided incentives to individuals for the adoption and use of electric vehicles (EVs), as well as to pay for the infrastructure seen as necessary to support a large-scale expansion of the EV fleet. The electrification of the transportation sector has the potential to require substantial upgrades to the electricity supply infrastructure in the state in order to maintain the reliability of electricity supply. A key input into the reliability planning process is an accurate picture of the level and timing of electricity demand that will be devoted to EV charging. Despite an aggressive electrification policy, there remain substantial gaps in our understanding of when, where, and how consumers charge their EVs.

The state's current estimates of EV charging (e.g., CEC 2019a and CEC 2019b) are based on charging patterns among electricity users who have a dedicated meter for their EV in addition to their normal household electricity meter. Importantly, however, customers are not required to install such an EV-dedicated meter when they purchase an EV. In fact, more than 95% of households with EVs do not have such a dedicated meter. Moreover, it is extremely unlikely that households with dedicated meters represent a random sample among all households with EVs. There are strong reasons to believe that these households are fundamentally different than the average California household that has purchased an EV. This means that the EV charging patterns captured by these meters may differ substantially from those of the average EV-owning California household.

In this report, we summarize the first phase of a project that represents the first attempt to rigorously estimate the causal effect of EV adoption on electricity usage for the average EV owner in California. To do this, we obtained hourly electricity usage data from all three investor-owned utilities (IOUs) and used econometric approaches to examine load before and after EV adoption. Our preliminary results suggest that, consistent with non-random selection into dedicated metering, home charging is somewhat different at the average EV-owning household than at households with EV-dedicated meters. Households that have enrolled in programs for EV eligible rates but are not separately metered, increase their consumption somewhat less than what is measured at households with EV-dedicated meters.

An important limitation of our current analysis is that we, like California's IOUs, do not observe household-level EV ownership. This means that our preliminary analysis documented here rests on two imperfect approaches: using households on EV rates (but without dedicated meters) to estimate the effects of EV adoption on EV load; and using aggregate data on census-block-group level energy consumption and car adoption. Though these results are steps in the right direction, making precise claims about the effects of EV adoption on electricity load will require household-level data on EV adoption.

1. Introduction

Since the passage of Assembly Bill 32 in 2006, the state of California has pursued increasingly ambitious policies aimed at reducing overall greenhouse gas (GHG) emissions. Since 2006, California GHG emissions have declined by almost 100 MMTons CO2e per year and the state is on target to easily meet AB 32's 2020 emissions reductions targets (Borenstein, et al. 2019). However, the majority of these reductions have been achieved in the electricity sector. Emissions from the transportation sector, currently responsible for over one-third of California's GHG emissions, have been rising since 2014.

With California Senate Bills 32 and 100, the state has committed to aggressive new greenhouse gas (GHG) reductions through a strategy focusing on the electrification of the residential, industrial, commercial, and, most significantly, transportation sectors. In particular, the state has devoted substantial financial resources to a broad suite of policies aimed at electrifying passenger transportation.

An overarching strategy of transitioning transportation and other energy use applications to electricity has profound implications for the electricity sector. This sector has itself experienced massive changes to the profiles of both end-use energy consumption and production. Residential electricity demand has been flat or declining for a decade, and mid-day electricity demanded from the grid has declined significantly due to the expansion of residential rooftop solar production. Strategies promoting electrification of transportation, home heating, and other applications raise the prospect of additional massive shifts in electricity demand.

An accurate forecast of not just the amount, but the timing—or load-profile—of electricity consumption is necessary to perform the planning steps necessary to maintain the reliable supply and distribution of electricity. The California Public Utilities Commission oversees an evolving resource adequacy requirement imposed on all electricity suppliers requiring them to procure resources sufficient to cover their forecast peak demand plus a reserve margin. Planning at the transmission and particularly the distribution level has been focused on the location and timing of electricity demand in order to ensure electricity flows do not exceed

Despite the need for it, relatively little empirical evidence is available about the impacts that electrification has had on residential electricity consumption to date. Although California is now home to over 650,000 electric vehicles (EVs), less than 5% of these vehicles are charged at home using a meter dedicated to EV use. Infrastructure planning and the implementation of important policies such as EV incentive programs and the Low Carbon Fuel Standard have had to rely upon either survey data or heuristic approximations to estimate the amount and timing of electricity use devoted to EVs.

In this report, we summarize the first phase in a project that, to our knowledge, represents the first attempt to rigorously and empirically measure the impacts of EV adoption on household electricity consumption. We obtained hourly electricity consumption data from 2014 to 2017 for a purpose-built sample of 10% of the households in California's three large investor-owned utilities (IOUs): Pacific Gas and Electric (PGE), Southern California Edison (SCE), and San Diego

Gas and Electric (SDGE). We combine these data with census block group (CBG)-level EV registration data to estimate the impact of EVs on residential consumption.

We develop several methods for estimating the effect of EVs on residential load. We propose a preferred event study approach, in which we would 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 would enable 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 we do not have household-level data, this approach is infeasible. Instead, we turn to three alternative approaches. First, we use load at EV-dedicated meters to compute energy use. The benefit of this approach is that it is a direct measure of EV load; the cost is that the sample of households with EV-dedicated meters is small and likely highly selected. Second, we compare load at households before and after they switch to an EV tariff which does not require a dedicated meter. Again, this method has benefits and costs: the benefits are that there are many more of these households, and they are likely to be less selected than the dedicated-meter households. The main costs are that we cannot directly separate effects of EVs from effects of the rate structure itself, and these households are still selected. Finally, we propose an aggregated version of our preferred approach, whereby we use CBG-level data to estimate the effects of EV adoption on electricity consumption.

Our initial results indicate that EV load at the average household purchasing an EV could be somewhat different than the charging load directly measured at households with EV-dedicated meters. Further, while the vast majority of homes charging at dedicated meters occurs between midnight and 3 AM, our results indicate that other households are doing considerably more charging in the early evening period, more coincident with system net-load. The results of this study differ from those of studies based solely on EV-dedicated meters; however, imprecisely measured results—in this study and in general—lead to an inability to reject a variety of hypotheses. The distribution of load may be concentrated in slightly earlier hours for EVs without EV-dedicated meters, and therefore would have more impact on system conditions; but again there is a need for more statistical precision.

These results are the first step in a longer-term research agenda built around quantifying the effects of EV adoption on energy use in California. We plan to extend the analysis presented here to include estimation results from SCE and SDGE, as well as to further investigate the effects of EV usage on hourly consumption patterns, rather than simply looking at aggregate load. Perhaps most importantly, we are pursuing opportunities to obtain more detailed EV registration data that will allow us to move away from the selected and/or aggregated sample analysis presented here. Many of the extensions and improvements that we envision along these lines are feasible but necessarily fall outside the scope of this brief research grant.

2. Background

Over the last decade, California has experienced a sharp reduction in the GHG intensity of its electricity production. According to the Emissions Inventory maintained by the California Air Resources Board, GHG emissions from the commercial electricity sector (excluding industrial self-generation) have declined from roughly 120 MMTons in 2007 to just over 50 MMTons in 2017 (Borenstein et al. 2019).

At the same time, overall electricity consumption, after experiencing a sharp contraction during the financial crises and its aftermath, has been relatively flat. While at first glance, this appears to signal progress on the GHG front in the dimension of reduced intensity *and* per-capita consumption, the overall emissions picture is more complicated.

While electricity purchases from the grid have declined slightly over the decade, both natural gas and gasoline consumption have risen. These facts illustrate the challenging fact that the share of energy consumption has been shifting toward the more carbon-intensive fossil fuels. California policy and the State agencies that implement it are heavily invested in reversing that trend.

As described below, there are ambitious programs promoting the adoption and use of EVs. The growth in EVs is anticipated to be a primary contributor to a reversal in the decline of electricity consumption over the next decade. As illustrated in Figure 1, current forecasts from the California Energy Commission's (CEC's) 2019 California Energy Demand (CED) indicate a rise in consumption to over 320 TWh per year by 2030 (CEC 2018). Current charging by EVs is estimated to account for less than 1% of statewide electricity consumption in 2018, but is forecasted by the CEC to grow by up to 10 times over the next decade (CEC 2018).

While these figures may seem modest at first glance, it is important to note that they account for almost all the expected growth in the electric system over the next decade and that the timing of these charging loads could result in their comprising a much larger share of system net peak consumption (net of renewable, primarily solar output).

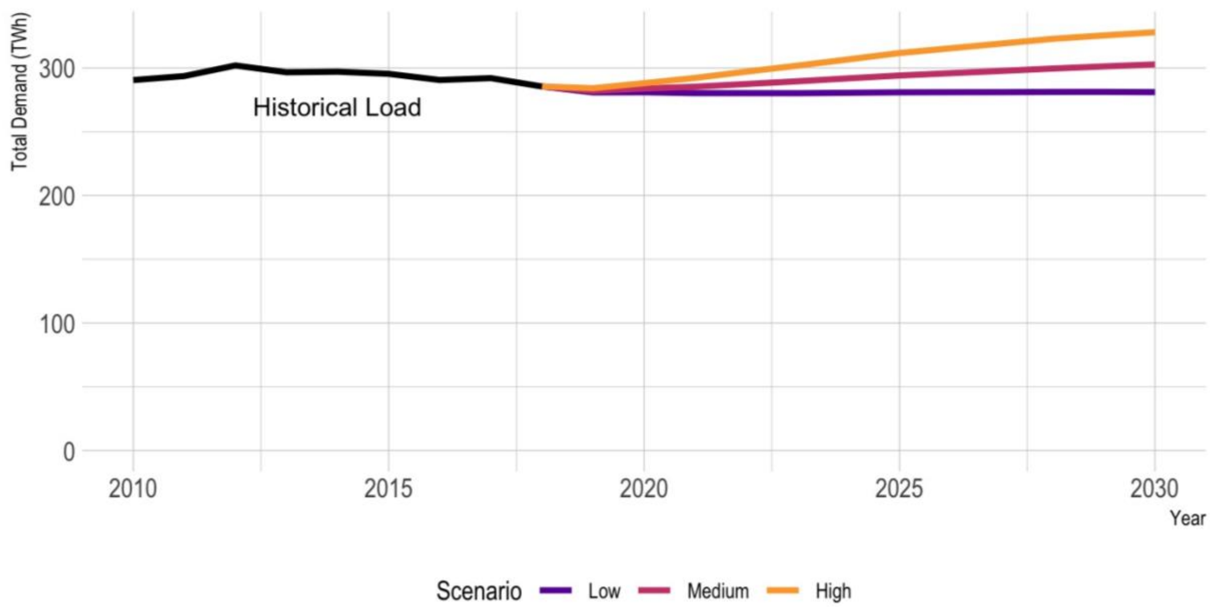

Figure 1. Load forecast estimates from the California Energy Demand report by the California Energy Commission (CEC 2018).

2.1 Electric Vehicle Policy in California

As mentioned above, transportation electrification is a central pillar of California's decarbonization goals. Despite some concerns over the ultimate carbon benefits of electrification (Holland et al. 2018), EVs do provide some benefits over conventional vehicles (Archsmith, Kendall, and Rapson 2015). These aspirations were articulated in the form of a 2012 executive order by Governor Brown to have 1.5 million EVs on the road by 2025, and a separate goal of 5.0 million EVs by 2030. Both the state and federal governments have adopted policies that are at least partly intended to promote the supply and demand of EVs. The California Zero Emission Vehicle (ZEV) Mandate generates credits for manufacturers that sell EVs and requires all manufacturers to either produce or purchase these credits. Similarly, the Corporate Average Fuel Economy standards offer an additional incentive to manufacturers that produce EVs.

On the demand side, there are large federal and state subsidies. As part of the American Clean Energy and Security Act of 2009, up to $1.5 billion in federally-funded tax credits were made available to consumers of each manufacturer. In California, the Clean Vehicle Rebate Project (CVRP) offers new EV buyers between $1,500 and $2,500 for new Plug-in Hybrid Electric Vehicles (PHEV) and Battery Electric Vehicle (BEV) purchases, respectively. These are often augmented by an array of other state and local incentives such as high-occupancy vehicle lane access and/or free or subsidized charging. Despite some concerns about the distributional impacts of these subsidies (Borenstein and Davis 2016), the California and federal incentives are clearly having an impact on EV adoption (Muehlegger and Rapson 2018). Through 2017, buyers of roughly 700,000 EVs nationwide claimed a total of an estimated $4.7 billion in federal subsidies. In California, 340,000 EVs have been purchased under the CVRP for a total of over $770 million in subsidies as of October 25, 2019.

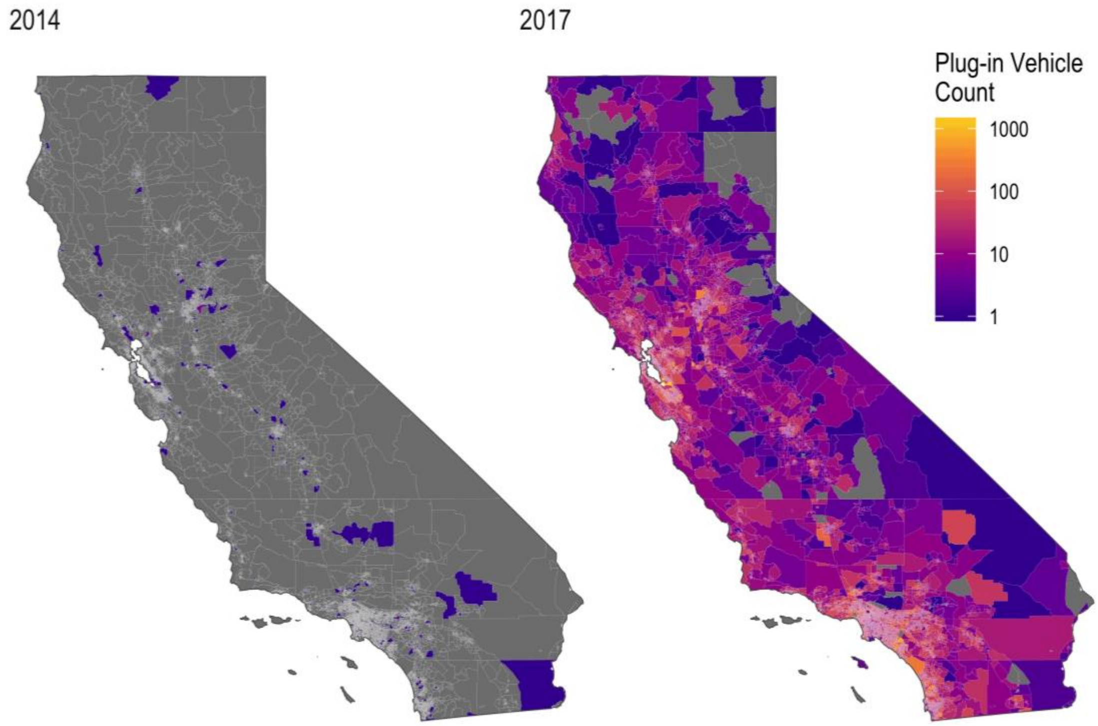

Figure 2. EV distribution and growth between 2014 and 2017 throughout California.

Figure 2 displays heat maps of where EV purchases were concentrated in California in 2014 and 2017. Most EV purchase activity occurs in cities along the coast, with major concentrations in the Bay Area, Los Angeles, and San Diego. At the end of our sample collection in December 2017, there are 423,297 plug-in EVs registered in California. This represents a 2.9% share of the 14.6 million passenger vehicles that were registered in California that year. Table 1 shows the number of EVs we observed in our sample (see 3. Data below for a description of our sampling approach) relative to the total number of EVs in the state.

While the stated goals for the adoption of EVs in the state are straightforward, understanding the translation of EVs on the road to electricity demand is a more complicated task. The challenges involved are described in more detail in the following section.

Table 1. EV Counts Within the Study by IOU, and the California Total.

Utility	EV Count
PGE	74,468
SCE	64,378
SDGE	3,125
Study Total	141,971
California Total	423,297

2.2 Measuring Electric Vehicle Electricity Consumption

By far the largest challenge in evaluating the impact of EV growth on the electric system is the lack of directly measured consumption data for residential home charging. Home charging of EVs does not require a separate meter or even separate equipment for low-voltage charging. Consequently, less than 5% of EVs are directly metered when charging at home (CEC 2019a). While charging at networks operated either by commercial charging businesses or vehicle manufactures such as Tesla is directly metered, the ARB estimates that upwards of 80% of EV households charge at home some or all of the time. Thus the vast majority of EV charging is currently unmeasured.[1]

Absent any detailed data on the customers without EV-dedicated meters, California planning and policy has come to rely upon projections based on the small share of households *with* EV-dedicated meters. This is problematic because these meters were not deployed randomly. They were chosen, at potentially high cost, to be installed by individual customers. This creates a significant empirical bias known as 'selection bias' that could cause projections based solely upon this non-random sample to be inaccurate and unreliable.

2.2.1 Why Metered Consumers May Be Different

There are several factors that could result in the sample of homes with directly metered EV load differing substantially from the overall population of EV-owning households. The main economic reason would be the prospect of gaining access to favorable electricity prices upon installing a separate meter. However, as described below, each utility offers potentially attractive tariff options to EV owning homes *without* separate meters. While these tariffs differ somewhat from those available to households with EV-dedicated meters, those differences do not appear to be economically substantial. On the other hand, installation of a meter requires an investment of at least a few hundred dollars, depending upon rebate offers and other incentive programs.

Absent a strong positive economic incentive to install an EV-dedicated electric meter, the remaining reasons are mainly behavioral or demographic. It is likely that households with EV-dedicated meters are those who value the access to the charging data itself. These may include "early adopters" with specific interests in closely following the performance of their vehicles. Because separate metering involves some up-front investment, households with these meters likely have higher incomes than the average EV household.

If the economic incentives (e.g., lower electricity prices) for separate metering were substantial, one would expect that the sample of households with EV-dedicated meters would charge more at home than would the average EV household. In other words, high charging loads would be the reason such households installed meters. However, given that the separately metered rates

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[1] The best data on EV charging use is probably 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.

do not appear to dominate other EV rate options, it is likely the behavioral and demographic elements mostly drive the choice to install a separate meter. If sub-metered EV households are comprised mainly of EV hobbyists, for example, it is quite possible that such households charge considerably less than the average household. There is already some evidence of the differences between the typical EV use and that of conventional vehicles (Davis 2019).

2.2.2 EV Rate Options

The interaction of electricity rates, vehicle adoption, and energy use is an area that deserves considerable attention. Despite the fact that many customers do not fully respond to complex rate structures (Ito 2014), the disparity between marginal electricity prices and social marginal cost in California is large enough that it could be a significant impediment to electrification (Borenstein and Bushnell 2018). Electricity prices may be influencing the decision to enroll in an EV rate and whether or not to install an EV-dedicated meter. All three investor owned utilities in California generally offer two rates: an EV rate for the whole house, whereby the entire house is on the time-of-use (TOU) rate, or the option to submeter the EV itself. All EV specific TOU rates are time-varying by season (summer and winter), and weekends and holidays. When the EV is submetered, only the EV meter is on the TOU rate; the rest of the household remains on their current tariff schedule. Over time, the EV rates at each IOU have changed names and structures. However, they generally include either a whole-house rate that is TOU or an EV-specific TOU rate that leaves the house itself on its existing rate.

EV rates are typically only offered to individuals with battery electric or plug-in electric vehicles, not hybrid electric vehicles.[2] Thus, a household wishing to make the transition to an EV rate need only demonstrate proof of EV ownership. In some cases, the distribution system may require an upgrade in order to support the increase in load. However, these are limited (see CPUC proceeding 19-IEPR-04). To obtain a designated EV (submetered) rate requires the purchase and installation of the meter itself. This can cost between a few hundred and a few thousand dollars.

3. Data

Our primary electricity data consist of individual interval metered electricity consumption from roughly 10% of households across the territories of the three large investor-owned utilities in California: Pacific Gas & Electric (PGE), Southern California Edison (SCE), and San Diego Gas & Electric (SDGE). From each utility, we requested data from 2014-2018, but data archive policies have delayed the transfer of 2014 data from some utilities. Our data are limited to single family residential households.

The electricity data include metered load (consumption) at the hourly level, the specific tariff (or rate) schedule in which the household is enrolled, indicators for service interruption, and

[2] The household TOU rate that is currently offered by SCE is an exception. It is open to all households, irrespective of EV ownership.

the census block group (CBG) in which the household is located.[3] The electricity data consist of hourly customer-level meter readings. In the case of households with an additional meter for their EV, we have meter data for both meters.

Our sample includes households on regular (non-EV) meters as well as those on two types of EV-specific electricity tariffs. Of course, the vast majority of customers are not on an EV rate at all. Most EV owners reside in this group, as do households that own only conventional vehicles. All three IOUs offer an EV rate that is available only to customers with EV-dedicated meters. In PGE and SDGE, there is a third rate type. In their territories, the majority of EV-rate customers charge via the master household meter, but on a rate that is available only to customers with an EV. Under this rate, EV load is indistinguishable from regular household load.

Our vehicle dataset was originally provided by the California Department of Motor Vehicles and consisted of the universe of registration records of plug-in hybrid vehicles (PHEVs) and battery electric vehicles (BEVs) in California from 2014–2017. The registration date and CBG designation enable us to observe when a new BEV or PHEV is registered in a given CBG over the four-year sample period.

Limitations imposed by the utilities restricted our data request to a 10% sample of residential meters in their service territories. The sampling methodology was intended to over-sample EVs while maintaining variation in two other variables of interest: income and frequency of service outages. The process of developing and implementing the sampling frame took several months and was adapted to meet the particular needs and constraints of the different IOUs. We will now describe these sampling methodologies in some detail.

3.1 Utility Data Sampling Approach

The ideal data set would include the universe of meters for all utilities across all years. However, as mentioned above, this is an immense amount of data that would create an unacceptable burden on the utilities providing the data. The next best option, from a scientific perspective, is to construct a sample that is both unbiased, in the sense that every group of interest is present in a representative proportion, and also has enough observations of the groups of interest to enable statistical tests on the data. Since the number of EV customers is relatively small, and the number of directly metered customers is very small, a completely random sample of 10% of the meters would risk missing most if not all directly metered customers. Therefore, we constructed a sampling method that accommodated the data constraints of each utility, and that combined the spirit of random sample with a stratification that would ensure a reasonable coverage of EV ownership and other demographic characteristics of interest. The final result is a sample of billing and meter data from each utility

[3] A typical CBG contains between 600 to 3000 people and is the smallest level of aggregation of households for which the US Census Bureau provides publicly available statistics on income. Population and other demographic characteristics can be easily obtained at the CBG level.

that included a large number of EVs, reflected the widest possible range of incomes that actively participate in the EV market, and include areas with variation in electricity reliability.

SCE and SDGE

The goal of the SCE and SDGE sampling method was to obtain the universe of meter-level data for a subset of CBGs whose number of residential accounts summed to represent 10% of each IOU's service territory. Our aspiration was for this sample to have an over-representation of EVs and service outages while also reflecting a wide range of incomes.

The sample methodology required two steps. The first step was necessary because of our desire to have CBG as the geographic unit of interest (for reasons described above). However, utility databases typically do not include CBG as a variable field. So in the first step we obtained account locations associated with the universe of residential accounts in a pre-selected subsample of ZIP codes, which is the geographic designation that utilities do have readily available in their database. We then geo-referenced each account, allowing us to assign each address to its CBG. In the second step we requested the final selection of CBGs to reflect our desired EV, outage, and demographic distributions, subject to the 10% sample size constraint imposed by the IOUs. The precise sampling methodology is available upon request, as these details require a precise explanation that is likely not relevant to the vast majority of readers.

PGE

The overarching goal of the PGE sampling strategy was the same as that in the other two IOUs: to capture consumers in high-EV-penetration areas and customers in low-reliability areas, while respecting the data constraint of capturing no more than 10% of households in the service territory. In PGE, we followed a slightly different sampling procedure than in the other IOUs, largely due to differences in what data we were able to collect from the utility before making our request.

With the PGE data set, we did all of our sampling at the ZIP code level, without being able to construct final samples at the CBG level. We again created a sampling frame weighted towards high EV penetration and low reliability. We were not able to stratify based on income with the PGE data. We created our sampling frame as follows:

- We ranked ZIP codes based on 2016 customer-hours of power outages based on a list provided by PGE. We selected ZIP codes on this list in descending order until we had accumulated 4% of the total population of the service territory. We sampled 100% of the population in each of these ZIP codes.
- We ranked ZIP codes based on EV penetration, and selected ZIP codes on this list in descending order until we had accumulated 4% of the total population of the service territory. We sampled 100% of the population in each of these ZIP codes.
- Finally, we selected a random sample of the remaining ZIP codes until we had captured 2% of the total population of the service territory, and sampled 100% of the population in each of these ZIP codes.

The first two samples constitute our main analysis sample from PGE; the third sampling group is for understanding how representative these samples are of the service territory as a whole. This approach leaves us with a total of 10% of customers in PGE's service territory, weighted towards high EV penetration and low reliability ZIP codes.

3.2 Data Description

The number of meters in each use category are in Table 2. The top three rows show how many EV-dedicated meters are present in each of our IOU data samples. In total, we observe almost 150 of these EV-dedicated meters. The low frequency of these meters likely reflects the costs of installation relative to less expensive alternatives such as charging at low voltage via the master meter, or charging outside the home. There are over 6,000 PGE customers on the bundled EV rate, and nearly 1,400 in SDGE territory. We know that EVs are owned by these households, but cannot separately distinguish EV load from other sources of electricity demand on those meters. Finally, roughly 99% of all the meters in our dataset are billed on non-EV tariffs. These households may or may not own EVs.

Table 2. IOU Meter Counts

Utility	Rate Type	2015	2016	2017
PGE	EV-dedicated Meter	13	54	40
SCE	EV-dedicated Meter	34	47	49
SDGE	EV-dedicated Meter	48	42	46
PGE	Bundled EV Meter	3,204	4,955	6,068
SCE	Bundled EV Meter	N/A	N/A	N/A
SDGE	Bundled EV Meter	756	1,063	1,383
PGE	Non-EV Meter	368,019	357,956	340,082
SCE	Non-EV Meter	260,249	280,531	295,595
SDGE	Non-EV Meter	198,994	215,543	215,396

Note: There are no bundled EV meters in SCE.

The highest penetration of EV tariff rates occurs on the coast, and especially in the Bay Area.

The level of use varies between meter type, both as a result of the potential presence of an EV and from other determinants of demand that may be correlated with the probability of purchasing an EV. Figure 3 graphs the average usage by meter type over time in each of the IOU service territory samples. In all cases, households with EV meters exhibit higher electricity consumption than households with other meter types. Moreover, the households with separate meters for their cars also consume more than that of the average household.

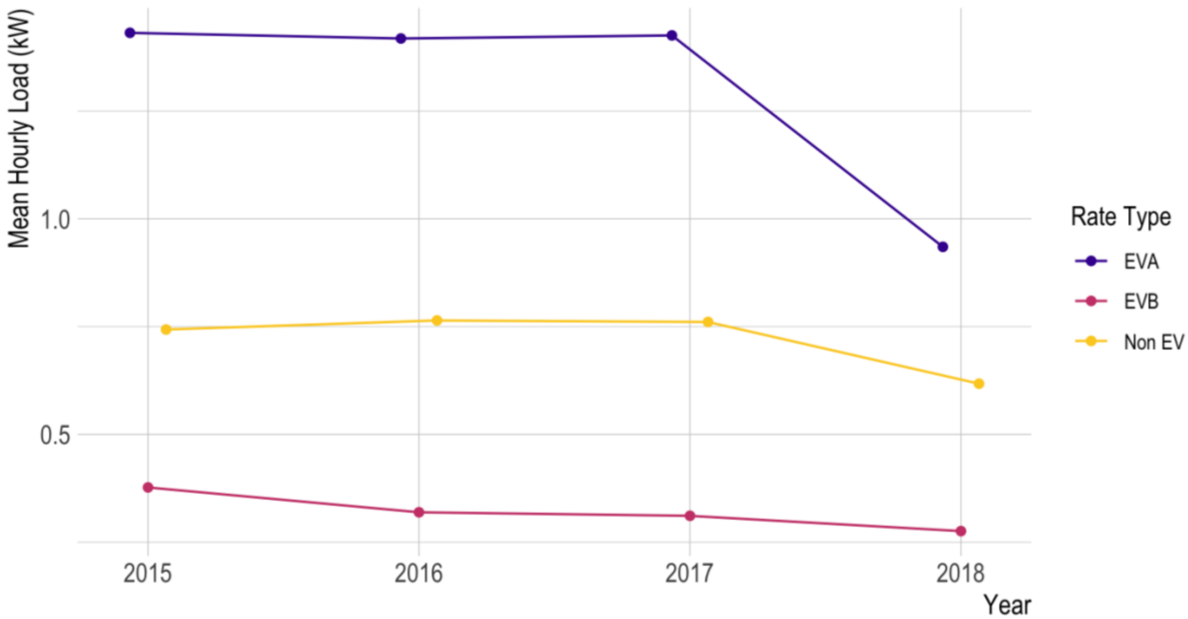

Figure 3. Meter load by IOU and meter type. EVA = bundled EV account; EVB = EV-dedicated meter account.

4. Empirical Approach

Our ultimate goal was to estimate the causal effect of EV adoption on electricity usage, both in aggregate and across the day. We are interested in estimating these effects for the average EV-owning household, as well as for EV-owning households with dedicated meters, to facilitate a comparison between our average estimates and those currently being used to set policy in California.

4.1 Preferred Approach

Our preferred approach to estimating the effects of EV ownership on electricity usage would be to use an "event study" research design, which allows us to compare energy use at an eventually-EV-owning household before and after they purchase their EV. This design also in principle allows us to include a variety of control variables (e.g., whether or not a household owns solar panels). The econometric model which corresponds to this event study design takes the following form:

$$kWh_{it} = \sum_{t=-T}^{T} \beta_t \mathbf{1}[\mathit{Time\ to\ EV\ adoption} = t]_{it} + \boldsymbol{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (1)$$

kWh_{it} is energy consumption in kWh for household i at time t. $\mathbf{1}$[Time to EV adoption = t]$_{it}$ is an indicator for "event time," such that $t = 0$ is the time that a household adopted their EV, $t = -5$ is five time periods prior to EV adoption, and $t = 5$ is seven time periods after EV adoption occurs, etcetera. $\mathbf{X}_{it}$ is a vector of additional controls. α_i and δ_t are household and time fixed effects: non-parametric controls for household-specific and time-period-specific effects, to ensure that we do not confound the effects of EV adoption with those of other household characteristics or events. ε_{it} is an error term. When we estimate this model, the β_t terms represent the causal effect of EV adoption on energy consumption. We can also enrich this specification by, for instance, estimating hour-of-the-day-specific treatment effects, to move beyond average effects towards load shapes. A substantial benefit of this approach is that we are able to estimate β_t terms for $t < 0$, that is, prior to EV adoption. This provides a useful credibility check for the specification: if we see treatment effects prior to an EV arriving, this is indicative of problems with the approach.

4.2 Data Limitations

We face an important data limitation that prevents us from estimating Equation (1) directly. While we have access to hourly household-level electricity consumption data, our data on EV adoption is much more limited. In particular, we do not observe household-level data on EV ownership, nor of the timing of that EV adoption. Instead, we only observe EV adoption at the CBG level. As a result, we cannot compare household *i*'s electricity consumption to itself before and after EV adoption—since we cannot directly measure which households actually adopted EVs and when—which is the goal of our preferred approach.

To make progress with the data that we do have, we performed three distinct analyses, leveraging the institutional details of California EV policy to guide our approaches. However, ultimately providing a convincing estimate of the effect of EV adoption on load for the average EV-owning household will require more data.

Our first two approaches look at energy consumption for households that we know have EVs: first, households with EV-dedicated meters, which form the basis for current load forecasts in California; and second, households on non-EV-dedicated meters and electricity rates. In our third approach, we use our aggregated data to estimate effects of EV adoption on energy use at the CBG level.

4.3 EVB Household Approach

Just like the existing California policy approach, our first estimate of the effects of EV ownership on electricity consumption comes from households who have chosen to install EV-dedicated meters. We denote these households as "EVB" households, reflecting the name of their rate schedule in the PGE service territory.[4] Because these households have dedicated meters, our approach to estimating the effects of EV adoption on energy usage for these households is very straightforward. We simply compute:

$$kWh_{it}^{EV\,B} = kWh_{it}^{EV\,B\text{ meter}} \qquad (1)$$

[4] Both SCE and SDGE also have rates that require households to install EV-dedicated meters, though these rates go by other names in these and other utilities. For notational convenience, we call all households across all utilities that have EV-dedicated meters "EVB households" in this report.

That is, we attribute all electricity used on the EVB meter to the EV. The benefit of this approach is that it is simple and measured with limited error. The cost of this approach, as discussed above, is that we believe that EVB households are different from the average EV owning household: only approximately 5% of EV owners choose the EVB rate, and these households appear to have different energy consumption patterns than households without these dedicated meters, as shown in Figure 3. Importantly, as shown in Table 2, in our 10% sample of each service territory (again, weighted towards high EV penetration), we only observe approximately 150 households with these dedicated meters.

4.4 EVA Household Approach

To understand the effects of EV adoption on energy use for a broader sample of the population than EVB households alone, we turn to other households that we know have EVs. Both PGE and SDGE have an additional rate category for EV owners which denoted as EVA.[5] In order to enroll on the EVA rate, a household must own an EV, but, importantly, is not required to install an EV-dedicated meter. Unsurprisingly, even though SCE does not have an EVA rate, we see thousands of households on EVA rates, as compared to the 150 households on dedicated meters.[6]

Because the EVA households do not have dedicated meters, we cannot simply attribute all of their consumption to the EVs themselves. That is, these meters measure only the combined electricity consumption of the EVs and of the household overall. In order to estimate the effects of EV adoption for these households, we estimate two variants of the same estimating equation:

$$kWh_{it} = \sum_{t=-T}^{T} \beta_t \mathbf{1}[\textit{Time to EVA rate adoption} = t]_{it} + \boldsymbol{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{3}$$

and

$$kWh_{it} = \beta \mathbf{1}[\textit{After EVA rate adoption} = t]_{it} + \boldsymbol{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{4}$$

Equation (3) is very similar to our preferred approach, described by Equation (1). Equation (4) is a "differences-in-differences" approach. This is similar to the event study but allows us to summarize the results in a single estimate, rather than time-period specific estimates. Both of these specifications have a key difference relative to our preferred approach, detailed in Equation (1): we still do not observe when a household adopted an EV. Instead, we only observe when this household switched from a standard residential electricity tariff to an EVA tariff. This generates two important caveats for our analysis. First, the EVA rate is different from the standard household electricity tariff, and we cannot disentangle the effects of EV adoption from any price effects coming from the rate structure itself. Second, we still do not directly

[5] Again, we follow PGE's nomenclature here.

[6] SCE did have an equivalent to the EVA rate but recently stopped accepting new households onto this rate. As a replacement to its EVA equivalent rate, SCE now offers a general TOU rate that is open to all customers.

observe the timing of EV adoption—we only see the timing of EVA tariff adoption. This is likely to be an imperfect proxy for the timing of EV adoption, generating a measurement error in our variable of interest.

As with the EVB analysis, there are benefits and costs to this approach. The primary benefit of this approach is that the EVA customers are a group that we can identify as having EVs. Unlike the EVB customers, however, because these households do not have EV-dedicated meters, we can presume that the costs of switching to the EVA rate is substantially lower than the costs of switching to the EVB rate, so selection problems may be less severe with this population. We see two main challenges with this approach. First, while the selection problem is likely less challenging than with the EVB households, we still expect there to be selection onto the EVA rate: these households are again not a random sample of EV owners in California. Second, the caveats mentioned above are important impediments to interpreting these effects as the results of EV adoption alone.

4.5 CBG-Level Approach

Because both the EVB and the EVA approaches are limited to households that select these tariffs and may not be representative of the average EV household, we take a third approach where we aggregate our electricity consumption data to the CBG level to match our DMV records.

With this aggregated data, we estimate:

$$kWh_{ct} = \sum_{t=-T}^{T} \beta_t \mathbf{1}[\textit{Time to EV adoption} = t]_{ct} + \boldsymbol{X}_{ct} + \alpha_c + \delta_t + \varepsilon_{ct} \tag{5}$$

Again, this looks very similar to Equation (1) above, but with one important difference: the unit of observation is no longer the household, i, but instead the CBG, c, where $kWhct = \Sigma\ i \in c\ kWhit$.

This approach has costs and benefits. The major benefit of this approach is that our electricity data and EV data are now at the same level of aggregation, making it possible for us to estimate the effect of EV adoption *on average* on energy consumption, rather than relying on a selected sample of EV owners. The downside of this approach is that EV adoption decisions are made at the household level rather than the CBG level. Having only CBG-level data makes it impossible to control for household-specific characteristics or changes in usage over time, which reduces the credibility of this aggregate approach substantially relative to our preferred household-level implementation.

5. Results

In this section, we present empirical results corresponding to the approaches described in 4. Empirical Approach. We first summarize the load of EVB households, which directly translates to EV consumption; next we estimate the effects on load of switching to an EVA tariff; and finally, we estimate CBG-level effects of EV adoption on energy consumption.

5.1 EVB Households

We begin by summarizing the energy usage data of EVB households: consumers with EV-dedicated meters. As described above, because EVB households have dedicated meters, we can simply use consumption on these meters to compute EV load.

Table 3 presents summary statistics on hourly load for EVB meters in each IOU. We observe only a small number of EVB meters: fewer than 50 in each utility. On average, hourly load at these meters is 0.35 kWh/hour in PGE; 0.38 kWh/hour in SCE, and 0.28 kWh/hour in SDGE. However, these meters exhibit a wide range of usage: the 5th percentile of consumption in each territory is 0 kWh/hour, but the 95th percentile is above 2.9 kWh/hour in all three IOUs.

Table 3. Hourly load: EVB meters

Utility	Mean Hourly Load	SD	5th Percentile	95th Percentile	N
PGE	0.352	1.581	0	2.91	112
SCE	0.375	1.548	0	3.10	150
SDGE	0.282	1.160	0	2.96	141

Beyond average consumption, the hourly load shape is also policy relevant and merits further exploration. Figure 4 plots EVB meter load shapes in each of the three IOUs. We find that charging load is heavily concentrated at night in all three IOUs. Average EVB meter load rises above 1.25 kWh/hour between 9 PM and 3 AM, while daytime load is less than 0.25 kWh/hour. This pattern is particularly strong in the PGE territory, where the midnight to 3 AM period constitutes the majority of total residential charging activity.

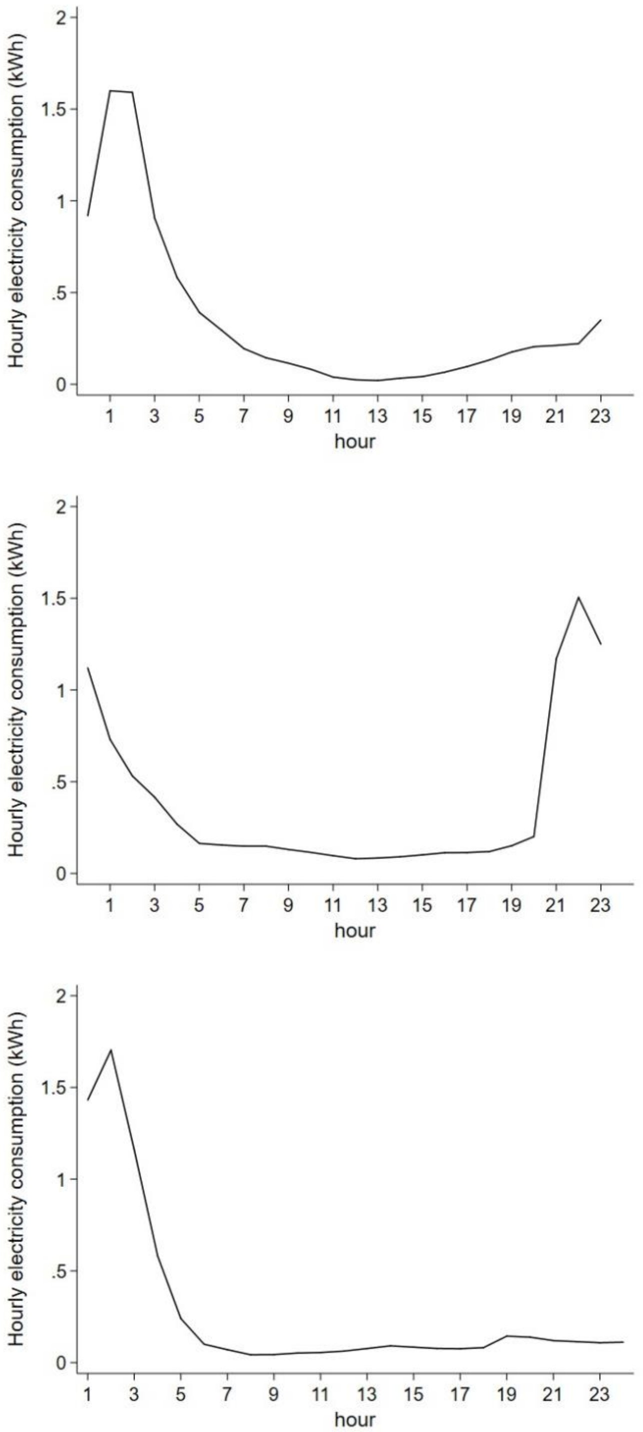

Figure 4. EVB meter load profiles: PGE, SCE, SDGE

The average household with an EV-dedicated meter uses approximately 8.4, 9.0, and 6.8 kWh per day on EV charging in PGE, SCE, and SDGE, respectively. Benchmarking this to estimates of EV efficiency of 30 kWh per 100 miles, these results imply that EVB households are using enough electricity to be driving between 160 and 210 miles per week.

5.2 EVA Households

We next turn to EVA households: consumers on EV tariffs, but without EV-dedicated meters. We first present basic consumption summary statistics for these households in Table 4 (note that SCE does not have an EVA-equivalent rate).

Table 4. Hourly load: EVA meters

Utility	Mean Hourly Load	SD	5th Percentile	95th Percentile	N (2017)
PGE	1.474	3.090	0	5.66	6,068
SCE	N/A	N/A	N/A	N/A	N/A
SDGE	1.314	1.968	0	4.95	1,383

Unsurprisingly, these meter usage numbers are substantially higher than the EVB meter consumption statistics shown in Table 3, because these include both EV usage as well as household usage. There are considerably more customers on EVA rates than on EVB rates: over 6,000 in PGE in 2017, and nearly 1,400 in SDGE. The PGE EVA customers use 1.5 kWh per hour on average, while the SDGE EVA customers use 1.3 kWh per hour on average.

Of course, we cannot attribute the full consumption of these meters to EVs. To make progress on separating EV consumption from the rest of the usage on these meters, we first simply examine consumption for a household before and after that household adopts the EVA rate. Table 5 shows the results of this exercise. Households in PGE use 0.55 kWh per hour more after switching to the EVA rate; SDGE households use 0.35 kWh per hour more after switching to the EVA rate. These results are striking: the change in consumption as households move to the EVA rate is quite a bit larger than load on EVB meters, particularly in the PGE service territory.

However, these results should not be directly interpreted as the causal effect of EV adoption. Switching to the EVA rate also changes the price schedule faced by a customer. Moreover, a simple before-after comparison may be confounded with other underlying trends.

Table 5. Energy usage: Switching to EVA rate

Utility	Before	After	Difference
PGE	1.176	1.724	0.548
SDGE	0.968	1.319	0.351

To enrich this analysis, we also provide graphical evidence on changes in energy consumption that are correlated with switching to an EVA rate. Figure 5 presents results for PGE, and Figure 6 presents results for SDGE.

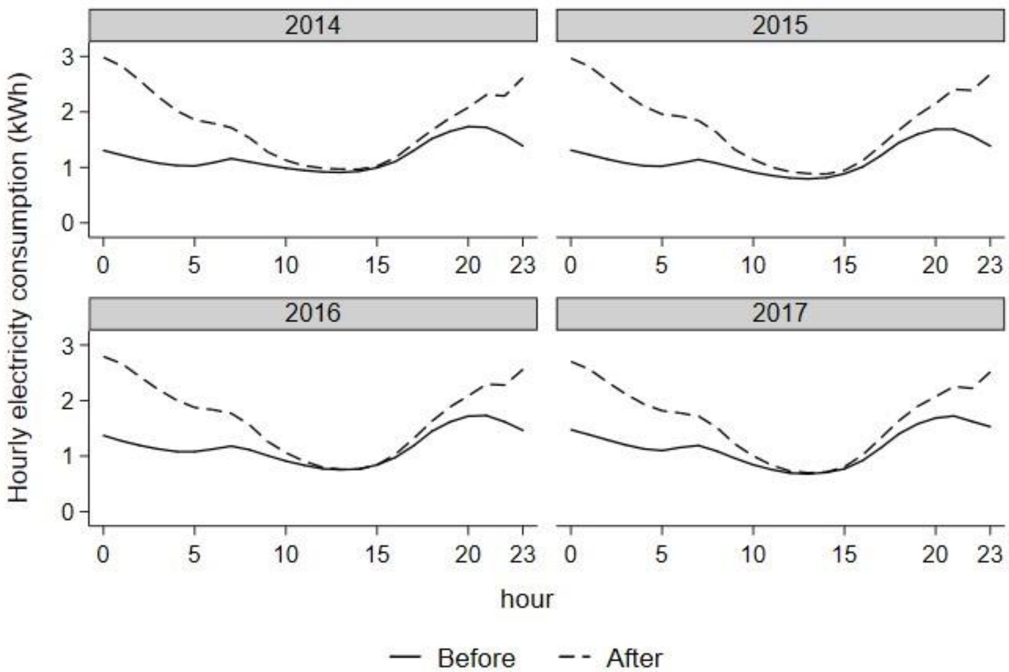

Figure 5. Energy consumption before vs. after switching to the EVA rate: PGE

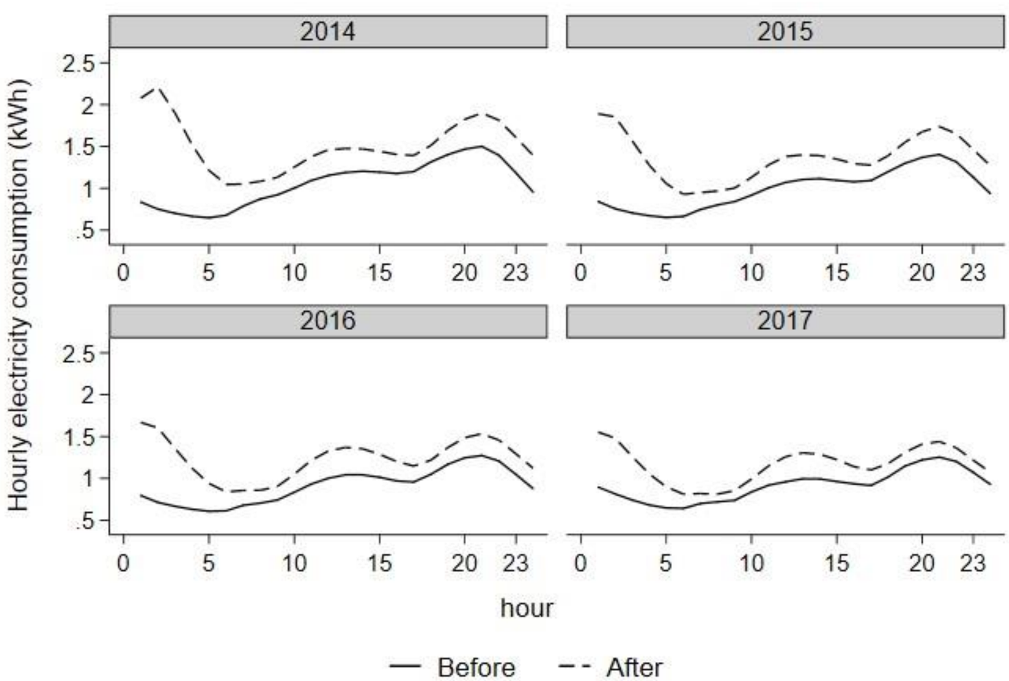

Figure 6. Energy consumption before vs. after switching to the EVA rate: SDGE

In both utilities, switching to an EVA rate is associated with higher energy usage. In PGE, across all four years of our sample, EVA households used substantially more energy at night after switching—consistent with the nighttime EV charging we observed in the EVB households.

To formalize this analysis further, we estimate the difference-in-difference model described in Equation (4) and the event study model described in Equation (3) for the PGE service territory. In both models, we include controls for household solar adoption, household-by-year fixed effects, household-by-month fixed effects, and week-of-sample fixed effects. We find a difference-in-difference point estimate of 0.30 kWh per hour (standard error of 0.02; statistically significant at $p < 0.001$). Figure 7 presents the event study results.

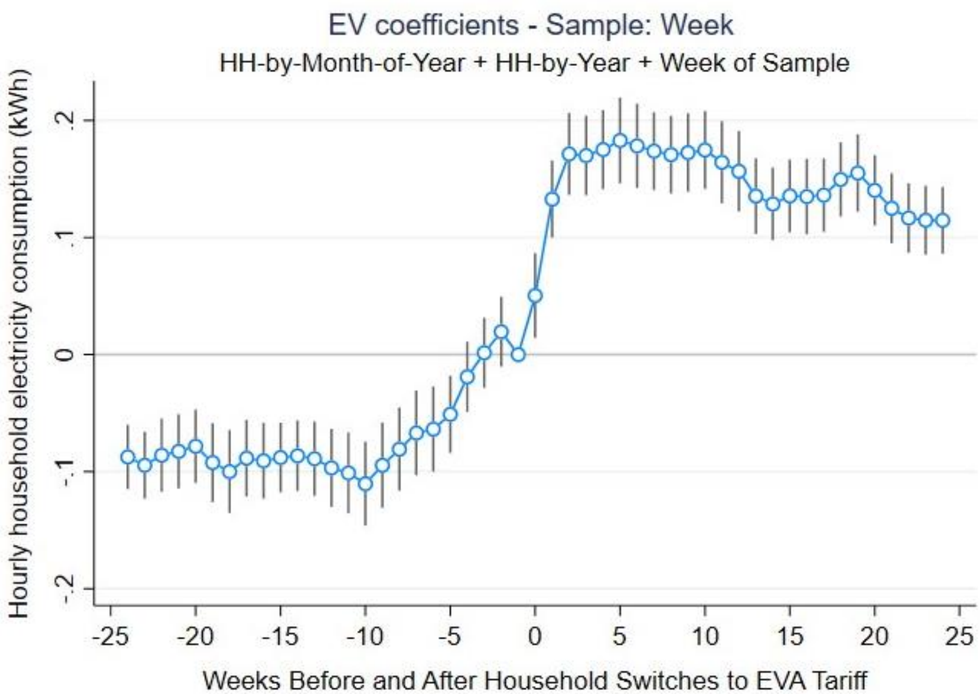

Figure 7. EVA event study: PGE service territory.

Figure 7 provides strong evidence that energy use increases sharply when households adopt the EVA rate. We find that households increase their consumption by 0.18 kWh/hour, relative to the week prior to switching to the EVA rate, using this approach. This number likely underestimates the true effect of switching to the EVA rate: as Figure 7 shows, 10 weeks prior to switching to the EVA rate, energy use is substantially lower than 1 week prior. This is likely related to the fact that households do not immediately switch to the EVA rate after adopting their electric vehicle. If we instead compare energy use 10 weeks prior to the EVA rate changeover to energy use 10 weeks after the EVA rate changeover, we estimate that energy use changes by 0.285 kWh per hour.

These estimates are smaller than the pure before-after comparison, suggesting that the before-after comparison is confounded with other changes and was biased upwards. They are also somewhat smaller—though not dramatically so—than the hour load estimates from the EVB meters. Again, using an estimate of 30 kWh per 100 miles, EVA households are using enough electricity to drive approximately 170 miles per week. Importantly, however, these estimates conflate any change in consumption due to EV adoption vs. being on a new tariff, with a different pricing structure than the standard household power prices in PGE's service territory.

5.3 CBG-Level Analysis

Finally, we aim to estimate the effects of EV ownership on electricity use for the *average* EV-owning household, rather than for a selected subsample of households on an EV-specific tariff. The lack of household-specific data on EV consumption makes this challenging. In the absence of these data, we designed an aggregated approach at the CBG level. We observe the date at which an EV arrives in a CBG, but we do not observe which household the EV goes to. To overcome this challenge, we aggregate our electricity consumption data to the CBG level and run the CBG-level event study regression described in Equation (5).

Using this approach, we do not see a distinct increase in energy usage at the CBG level when an EV enters the CBG. If anything, consumption appears to *decline* upon the addition of an EV, even after we control for CBG-by-month-of-year, CBG-by-year, and week-of-sample fixed effects. This suggests that, at the CBG level, the signal from an individual EV is indistinguishable from the substantial noise in CBG-level energy usage. Furthermore, our ability to pick out this signal is significantly hampered without household-level controls for usage patterns. In addition to being noisy, this CBG-level event study specification is quite sensitive to the set of control variables we include. Depending on the set of controls we include, we find estimates that range from negative effects of EV adoption to positive effects of EV adoption. As a result, we are not particularly confident in these event study analyses at the CBG level. Due to the preliminary and incomplete nature of these results, we choose not to include them here.

5.4 Results Summary

In this report, we document (measures of) the effects of EV adoption on energy consumption for three distinct groups of customers. First, we analyze households with EV-dedicated meters: EVB households. These households use 0.35 kWh per hour in PGE; 0.38 kWh per hour in SCE; and 0.28 kWh per hour in SDGE to charge EVs. In all three IOUs, the majority of charging is done during the nighttime hours. Next, we study the effects of adopting an EV tariff that does not require a dedicated meter (EVA tariff) on energy use in the PGE territory. We find that switching to an EVA tariff causes an approximately 0.30 kWh per hour increase in energy consumption—somewhat smaller than EVB consumption in PGE. However, neither of these analyses is adequate on its own. The EVB households are likely to be an extremely selected sample of EV owners, since switching to an EVB rate requires a considerable financial investment. The EVA households are also likely selected, and, moreover, in this approach, we cannot distinguish between changes in consumption coming from EV adoption and changes coming from a different electricity tariff. Finally, our CBG analysis produces results that appear not to make sense and do not pass standard empirical robustness checks. We believe that this is likely driven by a large noise-to-signal ratio in the CBG-level data. To fully understand the effects of EV adoption on energy use, we require better data: information on household-level EV adoption.

6. Conclusions

In this project we seek to estimate the level and timing of EV electric load. We combine hourly-level electricity meter data from 10% of California households with detailed EV registration data to develop three methods of estimating EV load. First, we examine EV-dedicated meters, which allow us to observe unambiguous measures of the load associated with EV charging at those meters. We learn two things: these EVs consume roughly 0.28-0.38 kWh per hour on average, and this load is concentrated between the hours of midnight to 3AM. Second, we examine household master meters that experience a switch onto an EV tariff during our sample period. The associated change in load on these meters is somewhat different than the load on the EV-dedicated meters. It is smaller in magnitude, which potentially reflects differences in the household composition between the two subsamples, and tends to occur earlier in the evening than the dedicated meter load. A statewide fleet comprised of vehicles with this load profile would be more difficult to absorb into the grid, both due to the timing and magnitude of charging patterns.

Our rich data also allowed us to explore methods with the goal of identifying average EV load at households on non-EV rates and without EV-dedicated meters. The overall population of residential electricity customers includes a small percentage of EV adopters who choose not to switch onto an EV tariff. In fact, the vast majority of EVs are registered to homes on a non-EV electric rate. Since we cannot directly match EVs to households, we instead attempted to estimate EV load at a more aggregated level (census block groups comprised of 600-3000 people) using information about when an EV is registered to a household in this neighborhood. This method proved empirically challenging. The noise-to-signal ratio of this data was too high to reach any reliable conclusions.

Myriad policy-relevant research questions remain unanswered in this setting. Significant societal benefits would result from continued support for sharing detailed vehicle registration and electricity meter data with researchers. In the present data setting, we’re able to learn with confidence about the activity at two types of EV meters. Unfortunately, the vast majority of EVs are at different types of meters, and researchers’ ability to see at this fine level of resolution requires two sets of household-level datasets: metered electricity consumption and vehicle registration. We encourage the continued support for data sharing under nondisclosure and security agreements that enable research that provides valuable input for policy decisions, such as studies of when, where, and how much people charge their EVs.

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