



Empirical grid impact of in-home electric vehicle charging differs from predictions^{*}

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ABSTRACT

Accurate assessment of the impact of electric vehicle (EV) charging on the electric grid is critical for energy policymakers to design efficient EV subsidy programs as well as to provide reliable electricity infrastructure. Despite the fact that 80 % of EV charging is conducted with residential in-home chargers, very few empirical studies have examined the load and environmental impact of residential EV charging based on actual electricity consumption data. Our paper fills this critical gap in the literature, applying a difference-in-differences approach to high frequency smart meter data of about 1600 EV homes from 2014 to 2019 in Arizona, United States. First, we find that the electricity demand during the system peak hours from 6 to 8 pm in summer can increase by 7–14 % at an average household with in-home EV charging. Second, EV households respond to electricity pricing signals by increasing their charging in lower-priced off-peak hours within the EV-specific time-of-use (TOU) pricing. Third, we find evidence of rebound effects in driving that lead to a reduction in home-electricity consumption in certain hours of the day. Lastly, we show that our empirical estimation of the grid impact due to in-home EV charging is different from that predicted by existing simulation models due to factors such as consumer behaviors. Such deviations between predicted and actual behaviors imply potential adjustment of relevant policy interventions.

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1. Introduction

Various types of financial incentives exist for adopting electric vehicles (EVs) and installing in-home EV chargers such as tax credits and direct rebates. A key motivation for such financial incentives is that EVs can electrify the transportation sector, and electrification is essential for decarbonization (Steinberg et al., 2017). According to the 2018 data, the transportation sector is the largest sector for greenhouse gas (GHG) emissions in the US, having exceeded the utility sector in 2017 (US EPA, 2019). The transportation sector is also responsible for emissions with negative health impacts, such as carbon monoxide,

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particulate matter, nitrogen oxide, non-methane organic gases, and formaldehyde. By electrifying vehicles, combined with the supply of electricity with clean and renewable energy sources, the emissions in the transportation sector can be reduced.

Electrifying vehicles has other potential benefits. Consumers can potentially save on expenditure on transportation fuel. EVs and in-home chargers, combined with electricity price signals, can also serve as a demand-side management strategy. EV owners can charge their EVs during off-peak hours with lower electricity prices to help flatten the electric load so that the grid operators have less pressure to ramp up power plants and meet sharp increases in demand during peak hours. The potential social benefits (reduced carbon and environmental emissions, and benefits to help the electric grid operations) warrant subsidies for EVs and the EV chargers.

The adoption of EVs worldwide has increased dramatically in the recent few years. In the United States, the projected number of EVs on road will reach 18.7 million, sharing about 7% of all cars and light trucks on road in 2030 (EEI, 2019). The wide adoption of EVs can have a significant impact on the electric grid (Muratori, 2018) and the associated environmental pollution (Holland et al., 2016). If EV charging adds to the electricity demand during electric grid system peak hours, this will create pressure on the electric grid infrastructure and implies grid expansion. EV charging in other hours can also have important implications for capacity planning and grid management.

Accurate assessment of the impact of EV charging is critical for energy policymakers to evaluate the EV adoption subsidies because the calculation of the positive externalities resulted from EVs relies on the estimation of the impact of EV charging on the electric grid. This paper focuses on the empirical analysis of the impacts from residential EV in-home charging on the electric load profile and how such impacts respond to various electricity price plans. Analyzing the impacts of residential EV charging is critical because residential charging accounts for about 80 % of EV charging among all charging methods, including public, commercial, and workplace charging (Charging at Home, 2021).

Most existing studies on residential EV charging and electric load profiles are simulation-based studies without using actual consumer behavior and electricity consumption data. Earlier simulation-based studies are helpful to predict the impact of residential EV charging on electric load profiles (Khemakhem et al., 2020; Harris and Webber, 2014; Paevere et al., 2014). Muratori (2018) adopts a bottom-up simulation modelling and finds that uncoordinated residential PEV charging can significantly change the load shape of residential consumers. Another study (Clement-Nyns et al., 2010) uses simulations to estimate that the PEV penetration rate of 30 % will increase the peak load at the residential distribution transformer level by 50 %.

Simulation-based studies have important common limitations as discussed in Muratori (2018): (a) assuming that PEVs are charged in a certain way (e.g., mostly in off-peak hours) and (b) using an average and pre-determined charging profile for all consumers in the models. As discussed in previous studies, actual consumer behaviors and technological performance can deviate from theoretical and simulated predictions (Qiu et al., 2021; Liang et al., 2020; Qiu et al., 2019; Liang et al., 2018; Fowlie et al., 2018; Qiu and Kahn, 2018; Zivin and Novan, 2016). Empirical studies can overcome these limitations by using actual data on behaviors and electric load profiles without the need to make assumptions on such behaviors (Lee et al., 2020).

Despite the fact that 80 % of EV charging is through in-home chargers, empirical studies examining residential EV charging based on actual electricity consumption data are very scarce. There are only two studies. Burkhardt et al. (2019) use data from 43 EV homes in Austin Texas to examine the impact of electricity pricing on residential EV charging behaviors. Compared to Burkhardt et al. (2019), we make two meaningful contributions. First, our larger sample size (about 1600 EV homes) should provide more representative estimates. Second, we adopt a study design (a difference-in-differences (DID) approach) more suitable for evaluating the causal impact of EV charging on load profiles. The second study, Burlig et al. (2021), uses EV registration data to link EV adoption timing with household electricity consumption data in California. Their study has a larger sample (about 57,000 EVs) than our study. While empirical evidence on residential EV charging is scarce, more empirical studies on public charging have been done. For example, (Jenn, 2020) analyzes high resolution empirical charging data at public charging stations of EVs that provide ride-hailing services (such as Uber and Lyft) in California, and finds that the associated environmental benefits are three times higher than the EVs in regular vehicle usage.

Our study provides a unique contribution to the literature in the following aspects. First, our study focuses on a different jurisdiction, the Phoenix metropolitan area, Arizona. Our study region and that of Burlig et al. (2021) differ significantly in terms of climate. Based on the International Energy Conservation Code, the study region of Burlig et al. (2021) and ours belong to different climate zones (IECC, 2020). Phoenix metropolitan area, a city built on desert, is known for its hot climate. Engineering studies have shown that hot climate can have a negative impact on EV battery performance (Samadani et al., 2016). Thus, the EV charging behaviors and the impact on electricity consumption in our study region will be different compared to the EV households in California. Understanding such empirical impact of EV charging in different jurisdictions can help researchers and policymakers better evaluate EV's impact. Second, in our study we were able to obtain the variation in retail tariffs across customers. This allows us to examine the impact of different electricity pricing plans such as time-of-use pricing on EV in-home charging behaviors. We find that pricing plays a significant role in influencing EV consumers' in-home charging patterns. Third, we conduct a back-of-envelope calculations of the environmental benefits, private savings, and reduction in generation costs from EV in-home charging using our empirical estimates. These benefits and costs from empirical estimation are different from those using engineering simulation estimates.

To summarize, there is a limited amount of empirical studies on the impact of residential EV charging on electric load profiles using a large sample of EV consumers. Our paper fills this critical gap in the literature by using high frequency smart meter data of about 1600 EV homes from 2014 to 2019 in Arizona, United States. Our main empirical method is to use fixed effects panel regression to control for confounding factors such as consumer-specific characteristics (e.g., building and

household attributes) that can impact both the adoption of EVs and EV pricing, and the electricity consumption behaviors. We also conduct a set of robustness checks to further help eliminate any potential biases, including zip code-year fixed effects, adding group-specific time trend, using propensity score and coarsened exact matching, using only treatment group data, and using only post-treatment data.

We have four key findings. First, we find that an average household with residential EV charging can increase the electricity demand by 7–14 % during the system peak hours from 6 to 8 pm in summer. The system peak is the highest electricity demand for the whole year. A 10 % residential EV penetration rate in a single utility's service territory implies the need for a new natural gas power plant to meet the demand increase during the system peak hours. Second, we find that EV consumers respond to electricity pricing signals by increasing their charging time in super off-peak hours (11 pm–5am) within the EV-specific time-of-use (TOU) pricing scheme. Third, the magnitude of change in the electric load profile due to EV charging is different in our empirical estimates from the charging profiles obtained in the previous simulation studies. One of such behavioral changes is rebound effects in driving that lead to a reduction in home-electricity consumption in certain hours of the day. The rebound effects here mean that consumers drive more when they get an EV so they are out of the house more resulting in a reduction in consumption in certain hours. Such deviations between predicted and actual behaviors imply potential adjustment of relevant policy interventions. Lastly, we estimate the annual environmental benefit of EV in-home charging of \$101–113 per consumer and the annual private benefit from fuel cost savings of \$517–640 per consumer.

The rest of the paper is organized as follows. Section 2 presents a summary of the data and industry background information. Section 3 summarizes our empirical methodology. Section 4 presents the results of the empirical analyses. Section 5 discusses the implications for grid management, private and environmental benefits, comparison with simulation studies, as well as connections to broader literature. Section 6 concludes.

2. Program background and data

We study in-home EV charging in the Phoenix metropolitan area, Arizona, under the service territory of the utility company Salt River Project (SRP). SRP provided financial incentives for their consumers to report their EV charging status for an internal EV load impact study. More than 1600 EV customers self-reported their EV ownership and in-home charging status to SRP through this study, along with information on the types of chargers used and the charging start dates¹. We don't have the information on the EV model in our dataset. We also have access to the information of about 17,000 non-EV households which can serve as potential control homes. We know that these control homes do not have EVs because these are the consumers that were surveyed in SRP's residential energy technology survey in 2017 and they reported no EV in the survey. We randomly select a subset (2224) of the 17,000 non-EV homes as the control group. For each home, we have the hourly smart meter electricity data from 2014 to 2019. Since we examine the entire household electric meters, our estimated impacts are the changes in total electricity consumption of the household due to EV charging, which is important because EV charging can potentially induce behavioral changes such as using more or less of other electric appliances in the house.

The majority of the EV in-home charging consumers were on two types of electricity rates before they adopted the chargers. We call these base rates. These two “base rates” are: (1) an increasing block tariff (IBT, called E-23 rate in SRP's rate book) and (2) a time-of-use (TOU) rate (called E-26 rate)². Some EV consumers stay on their base rates while others switch to an EV-specific price plan – a specific TOU rate (called E-29 rate). For those who switched to the EV-specific price plan, a few months' lags exist between the date of EV charger adoption and the date of switching to the EV price plan. The increasing block rate IBT does not have different marginal electricity prices at different hours of the day. The marginal price of IBT experiences a sudden increase after the cumulative electricity consumption within a given month exceeds a certain threshold. The two TOU price plans have higher marginal electricity prices during peak hours, and lower prices during off-peak hours. The peak hours of the TOU base rate are between 2 pm and 8 pm in summer months, and are 5–9am & 5–9 pm in winter months. The peak hours of the EV-specific TOU rate has the same peak hours with one important difference: super off-peak hours from 11 pm to 5am when the electricity prices are very low (lower than the remaining off-peak hours) in all seasons to encourage charging at night. Table S1 in the Supplementary Information provides the details of these three rates.

We fully acknowledge the self-selection of EV adoption. In terms of the sample representativeness, the self-reported 1600 EV consumers can potentially be different from the other EV consumers who do not self-report their EV status. Unfortunately, since we do not have the household characteristics of these EV consumers, we do not know how or whether they are different. Since our paper uses a large sample of EV homes to estimate empirically the impact of EV charging on electric load, we think that such self-reported sample can still shed important light on such impact. To help alleviate the concern about

¹ To eliminate any potential concern about the measurement error of charging start date, we conduct a robustness check and drop the data 4 weeks before and 4 weeks after the reported EV charging start dates. Results in Supplementary Fig. S17 show similar results as our main analysis, indicating low likelihood of a measurement error.

² In our original analysis, we dropped those who switched rates to a different non-EV base rate. In other words, in our analysis, we only included those who always stayed on one of the two base non-EV rates, or those who were first on one of the two base rates and then switched to the EV rate after they started EV charging. As a result, the base rate switching did not happen in our analysis. However, to further alleviate this concern, we now go back to the raw data and check how many EV consumers switched between different non-EV rates. In total about 35.7% consumers switched between different non-EV rates. These consumers did not enter our analysis due to the confounding effects of the price plans. We conducted a separate analysis keeping the 35.7% consumers in the regression models. The results are listed in Supplementary Information Fig. S18. The results are similar to our main results.

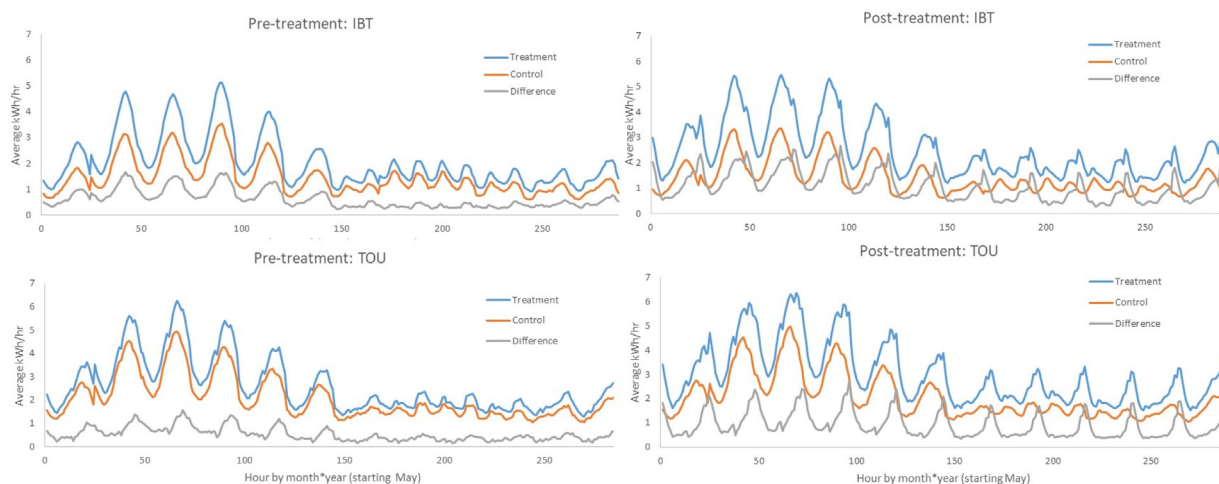


Fig. 1. The average hourly electricity consumption profiles of the treatment and control groups one-year before and after the adoption of EV charging. Notes: The electricity consumption by hour-of-day is averaged by month-of-year. Treatment means EV consumers and control means non-EV consumers. Difference = Treatment-Control. IBT is the increasing block base rate. TOU is the TOU base rate. The number of each type of consumers in this figure: IBT control consumers- 1315, EV consumers with IBT as the base rate - 876, TOU control consumers-909, EV consumers with TOU as the base rate - 813.

external validity, we match the zip code level characteristics to each EV consumer in our sample and compare our EV sample characteristics with that from the most recent nationwide Residential Energy Consumption Survey (RECS) conducted by Energy Information Administration (EIA, 2015). Results in Supplementary Table S11 show that our sample of self-reported EV consumers have similar education, income, and race profiles compared to the nationwide EV consumers sampled from the most recent RECS survey.

In our sample, compared to non-EV consumers, the EV consumers have higher education, higher income, and a lower percentage of the ethnic minority population. However, since we include individual household fixed effects and run DID analysis (Lechner, 2011), we can tease out any differences between households that are time-invariant such as wealth and environmental awareness. Also, as long as the control and treatment groups share parallel trends prior to the treatment, then DID analysis is still valid despite the differences in baseline levels. As will be discussed later, we conduct an event-study analysis to check for the parallel trends of electricity consumption between EV and non-EV consumers. We also conduct another analysis using propensity score and coarsened exact matching to find more comparable non-EV consumers.

Fig. 1 plots the average hourly electricity demand by hour-of-day and by month-of-year one-year before and after the treatment between the control (non-EV) and treatment (EV in-home charging) consumers. The treatment here is the start of EV charging. The start dates of the EV charging can be different for different EV consumers. Control consumers do not have the treatment (in Fig. 1, we randomly assign a hypothetical treatment date for each control consumer in order to create pre-treatment and post-treatment periods for these control consumers.) The pre-treatment load shapes between the treatment and control consumers show parallel trends in general. EV charging households on average consume more electricity than non-EV households. However, since the control and treatment consumers share parallel trends in electricity consumption, using panel regressions and difference-in-differences methods can help difference out the baseline differences in the levels of electricity consumption between the two groups. The post-treatment electricity consumption profiles show the increase in electricity consumption of EV consumers compared to non-EV consumers. The geographic distributions of the control and treatment consumers can be found in Fig. S1 in Supplementary Information, which shows that the treatment and control consumers are balanced in terms of locations. Table S2 in the Supplementary Information shows the summary statistics of the key variables in our analysis.

3. Methods

3.1. Study design

We use a difference-in-differences (DID) method to deal with endogeneity concerns. Since the adoption of EVs and in-home EV chargers is voluntary, there can be potential selection bias and omitted variable issues. For example, consumers who adopt in-home chargers might be those who are more environmentally-conscious and, therefore, they might be also more likely to save on their electricity consumption. To address these issues, we adopt fixed effects panel regressions to control for the unobservable variables that can cause the endogeneity issues. About 1600 EV owners started in-home charging during 2014–2019. We thus have the electricity data in both the pre-treatment and post-treatment periods for these EV owners, enabling a DID design. We checked for the parallel-trend assumption (as shown in the electric load profiles in Fig. 1 and in the event study analyses as discussed later) and confirmed that the electricity consumption profiles between the non-EV and

EV homes share parallel trends prior to the start of in-home charging. In addition, we conduct an additional analysis using propensity score matching and coarsened exact matching (as discussed in Section 4) to construct a control group that are similar to the EV consumers in terms of pre-treatment summer and winter electricity consumption. This matching approach can help eliminate any further potential concerns about the differential electricity consumption trends in the pre-treatment period of the EV and non-EV consumers.

There is also potential concern about the solar panel installation or other major changes in household consumption that can occur at the same time as the EV arrives, the so-called contemporaneous changes. Although not directly available from our dataset, based on SRP's 2017 residential energy technology survey, only 9% of EV households have solar panels. Also these solar panels may not have been installed around the same time of installing EV chargers. As a result, the probability of other major technological changes happening around the same time of adopting EVs should be very low. As will be discussed later, in a robustness check, we include a group-specific time trend to control for any time-variant unobservable differences between the EV charging and non-EV consumers, such as contemporaneous changes that can happen around the same time of adopting EV charging. In addition, we only included non-solar consumers or the pre-solar-adoption data of solar consumers in our analysis³.

3.2. Base panel regression models

A base panel regression model is

$$\text{kWh}_{ih} = \alpha_i + \sum_{H=1}^{24} \beta_H \text{EV_Charging}_{ih} * I_H + \gamma p_{ih} + f(\text{HDD}_{ih})\theta + f(\text{CDD}_{ih})\eta + \text{Day of sample} + \text{Hour of day} + \varepsilon_{ih} \quad (1)$$

where i indicates individual residential consumer; h indicates hour-of-sample; kWh_{ih} is the electricity consumption of consumer i in hour h . α_i is individual consumer fixed effects which can control for factors such as consumer socio-demographics, behavioral and awareness characteristics, and technology attributes that can influence both the adoption of EV charging and the electricity consumption behaviors. EV_Charging indicates whether a consumer has started in-home EV charging^{4,5}; I_H indicates hour-of-day; β_H measures the impact of EV charging on electricity consumption in hour H of the day. p_{ih} is the electricity price⁶. $f(\text{HDD}_{ih})$ is the spline function of heating degree days (calculated using 65 degrees) and $f(\text{CDD}_{ih})$ is the spline function of cooling degree days (calculated using 65 degrees); for the spline functions, we use 4 knots equally spaced based on percentiles of HDD and CDD; the hourly temperature data comes from meteoblue.com. Our rich day-of-sample (year-by-day-of-year) fixed effects can control for variations in electricity usage patterns at each day of our sample, which includes seasonal patterns and daily patterns that vary across years. Hour-of-day fixed effects control for hourly differences in electricity using patterns within a day. Note that we do not include holiday indicator or weekend indicator because these two indicators will be automatically dropped with the day-of-sample fixed effects included, which already capture the effects of a holiday or weekend. The standard errors in all our models are clustered at individual household level. Overall, our empirical analysis controls for time-invariant consumer attributes, temperature, seasonality, and daily economy-wide common shocks.

³ In our dataset, for each individual consumer, there are different types of meter data with specific identification codes. The types of meters relevant for our study include S, 0, and Z. Code S indicates the solar electricity generation meter. 0 and Z are house meters (meters that record household electricity consumption). Code 0 is for customer accounts before they acquired solar and Z is for accounts after adopting solar panels. A non-solar consumer will never have the meters S or Z showing up in our dataset. A solar consumer only had meter 0 before adopting solar panels. Thus, we can use meter type S and Z to identify the EV consumers who adopted solar panels. In our original analysis, we only included meter type 0 in all of our models; in other words, we only included non-solar consumers, or the pre-solar-adoption data of solar consumers. As a result, our main analysis would not be confounded by solar adoption. However, one might argue that EV consumers with solar panels might be different from EV-only consumers in terms of their behaviors even before adopting solar panels. Thus we add a robustness check, in which we remove the pre-solar-adoption data of EV consumers who eventually adopted solar panels (note that the post-solar-adoption data was not in our analysis in the first place). The results are consistent with our main results and are shown in Supplementary Fig. S5.

⁴ Note that this treatment variable indicates the start of EV charging, no matter it is through the dedicated EV meter or through the household master meter, because the EV household reported the EV charging start date as when they started charging the EVs.

⁵ In our setting, the treatment timing (EV charging and EV pricing) varies across different treatment consumers. According to Goodman-Bacon (2021); de Chaisemartin and D'Haultfoeuille (2020), using two way fixed effects model in such a setting is equivalent to calculating a weighted average of all possible two-group/two-period difference-in-difference estimators. If there are negative weights, the usual two way fixed effects linear model estimand may for instance be negative but in fact all average treatment effects on the treated (ATT) are positive, thus generating a biased weighted treatment effect. We use the algorithm developed by De Chaisemartin & d'Haultfoeuille (2020) to compute the weight attached to individual ATT in each group and period. The results are listed in Supplementary Table S12 and show that the number of negative weights are very small compared to the total number of ATTs. This indicates a low probability of biased ATTs estimated from our main two way fixed effects model.

⁶ There is a potential concern about the endogeneity of the electricity price, if the decision to adopt a new tariff is correlated with unobservable time-varying heterogeneity. We conduct an additional analysis removing the price variable, similar to the model specification in Burlig et al. (2021). The results are very similar to our main results. Please see Supplementary Fig. S6. To avoid the endogeneity issue of price level with the inclining block tariff, we do not construct the price based on cumulative electricity consumption within a given month. Instead, we use the average (not weighted) of all price levels of the inclining block rate of each billing season. One rationale for this is that consumers might not be able to monitor their hourly price precisely given the cost to search for such information.

We also analyze the impact of switching to EV-specific pricing on EV-charging homes' electricity consumption profiles. The following model is applied to the post-charging only data of EV charging consumers only. This way the pre-treatment period of the pricing analysis is after adopting EV charging but before switching to EV pricing.

$$\text{kWh}_{ih} = \alpha_i + \sum_{H=1}^{24} \beta_H \text{EV_pricing}_{ih} * I_H + \gamma p_{ih} + f(\text{HDD}_{ih})\theta + f(\text{CDD}_{ih})\eta + \text{Day of sample} + \text{Hour of day} + \varepsilon_{ih} \quad (2)$$

where *EV_pricing* indicates whether an EV consumer has switched to EV-specific pricing. All other variables have the same definitions as in Eq. (1). We acknowledge that switching to the EV rate is also self-selected. To deal with potential self-selection issues of EV pricing, we use consumer-fixed effects to control for any time invariant confounding factors such as sensitivities to pricing. We also conduct event study analysis to check for the parallel trend assumption for the DID analysis of the impact of EV pricing.

3.3. Event study models

We conduct an event study analysis for two purposes: to estimate the average hourly net electricity consumption change post-charging, and to test the parallel trend assumption (the EV charging and non-EV consumers are comparable in terms of exhibiting similar trends of electricity consumption prior to the treatment). The parallel trend assumption is important to justify that the estimated impact of EV charging adoption from our DID regression is not biased due to any systematic differential trends between EV charging adopters and non-adopters. The following event study model is applied to the two separate samples with different base rates:

$$\text{kWh}_{ih} = \alpha_i + \sum_{w=-15}^{15} \beta_w 1[\text{Time to EV charging adoption} = w]_{ih} + \gamma p_{ih} + f(\text{HDD}_{ih})\theta + f(\text{CDD}_{ih})\eta + \text{Day of sample} + \text{Hour of day} + \varepsilon_{ih} \quad (3)$$

where *h* indicates hour-of-sample; $1[\text{Time to EV charging adoption} = w]_{ih}$ is a dummy variable indicating the week to the EV charging adoption which the hour-of-sample *h* falls into. We analyze the 15 weeks prior to and 15 weeks after the adoption.

3.4. Calculation of the costs and benefits of EV in-home charging

We conduct a back-of-envelope calculation to estimate the reduction in generation costs, environmental benefits, and private savings from EV in-home charging. To calculate the reduction in generation costs, we use the largest increase in hourly electricity consumption from 6 to 8 pm due to EV charging in the summer months, during which the system peak load generally happens in our study region. We multiply this increase in electricity consumption by the number of EV households assuming a 10 % EV diffusion rate to calculate the increase in electricity generation capacity needed. We then estimate the monetary cost associated with this additional generation capacity using data on the costs of natural gas power plants from EIA.

To estimate the environmental benefits, we use the marginal environmental damage factors from electricity generation at hourly level in our study region from [Holland et al. \(2016\)](#) which consider the damages from CO₂, NO_x, SO₂, and particulate matter by hour of day. We multiply these damage factors with our estimated changes in electricity consumption from EV charging to obtain the environmental damages from driving EVs. We then use the estimated changes in electricity consumption to infer the mileage driven by EVs, convert the mileage to be driven by a typical gasoline car, and then infer the environmental damages from driving the same mileage from a gasoline car. The difference between the environmental damages from driving an EV versus a gasoline car is the environmental benefit from EV in-home charging.

To estimate the private bill savings, we first calculate the extra electricity expenditure by multiplying the hourly electricity price with the hourly increase in electricity consumption due to EV charging. Then using the inferred driving mileage, we calculate the expenditure on gasoline. The difference between the expenditures on electricity versus gasoline is the private benefits from bill savings. Details of these calculations can be found in Section 5.

4. Results

4.1. Impact of EV charging on electric load profiles

We estimate how adopting EV in-home chargers can impact the electricity consumption by hour of day and thus the electric load profiles. As discussed in the program background and data section, the majority of EV in-home charging consumers were on the two base electricity price plans (IBT and TOU) before they adopted the chargers. We analyze the impacts for consumers with these two base rates (an IBT/non-TOU and an TOU rate) separately. The control group for each base rate treatment group also shares the same base electricity rate. In other words, for the EV treatment group with IBT or TOU as the base rate, the control consumers always stay in IBT or TOU, respectively, in our study period.

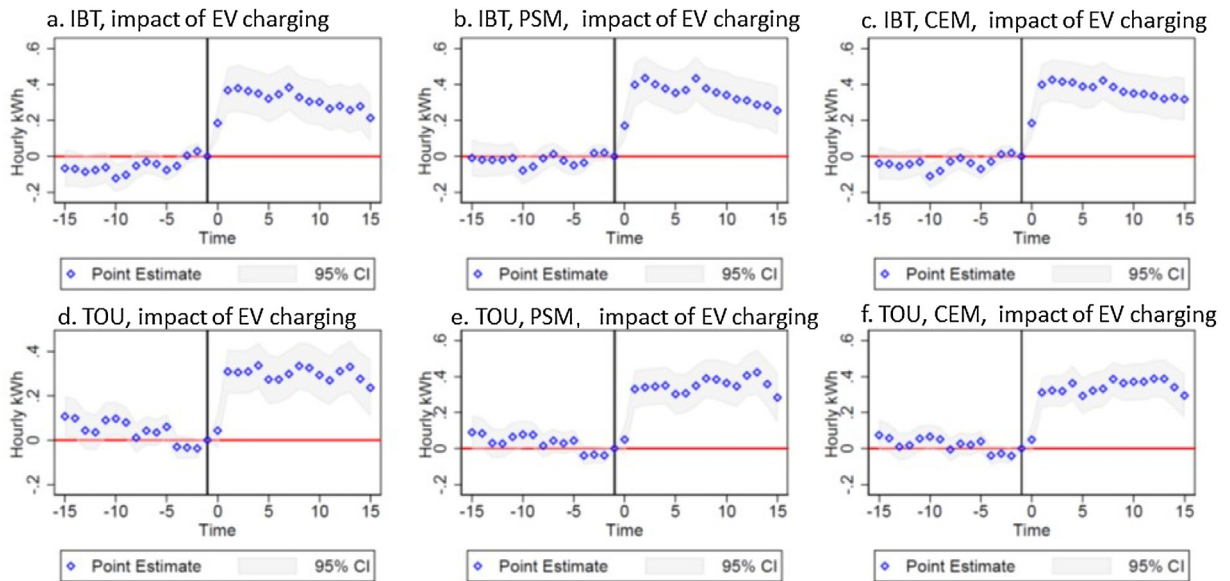


Fig. 2. Event study analysis of impact of EV in-home charging adoption. Notes: PSM is for the samples after propensity score matching. CEM is for the sample after coarsened exact matching. X-axis measures the number of weeks to EV charging adoption. Weeks prior to the adoption are indicated by -15 to 0 in the X-axis, and weeks after are indicated by 0 to 15. Y-axis measures the difference in the average hourly electricity consumption between the treatment and control groups; the difference is normalized to be zero at time -1. IBT and TOU indicate consumers with these two different base rates.

• Event study results

Fig. 2 shows the event study results of impact of EV charging. The average hourly electricity consumption increased significantly after adopting the chargers in both of the two base rate cases. In terms of the parallel trend, the difference between the EV and non-EV consumers prior to the EV adoption is in general not statistically significant.

For the event study analysis of samples with matching (panels b, c, e, and f), the pre-treatment parallel trends are clearly satisfied given the close-to-zero coefficients in the pre-treatment periods and the non-statistical-significance of these coefficients. As we will show later, the results using matched samples are very similar to the results using unmatched samples, helping eliminate any concern about the different trends in the pre-treatment periods of the unmatched sample. In the event study analysis of the samples without matching, although in the pre-treatment period the coefficients are generally not statistically significant (indicating no differential trends in the pre-treatment period), the non-zero values of some coefficients are worth further checks. To further eliminate any potential concerns about the differential trends in the pre-treatment period of the unmatched sample, in one robustness check, we include a group-specific time trend (an interaction term between the treatment group indicator and the day-of-sample variable) to control for any potential differential trends in the pre-treatment period, a method similar to the one used in Davis et al. (2014).

Based on Fig. 2, on average, EV charging increases electricity consumption by 0.31 kW h/hour, or 7.59 kW h/day for IBT consumers (approximately 15 % increase in average daily consumption). For TOU consumers, EV charging increases electricity consumption by 0.30 kW h/hour, or 7.18 kW h/day (approximately 12 % increase in average daily consumption). This is higher than that from Burlig et al. (2021) in which approximately 0.121 kW h per hour or 2.9 kW h per day of increase was observed. However, our estimates are similar to the 7.2–8 kWh per day increase reported by California Energy Commission (CEC, 2019) which relies on residential charging data. This again highlights the importance of conducting such empirical analysis in different regions.

• Impact for consumers with the base rate being increasing block pricing

For consumers whose base rate is the increasing block tariff (IBT), the impact of EV in-home charging adoption is illustrated in Fig. 3 (Detailed coefficients and model results can be found in Supplementary Information Table S3). In this figure, three rows present graphs of “All seasons”, “Summer”, and “Winter,” while three columns present groups of “all consumers,” “consumers who did not switch to the EV rate,” and “consumers who switched.” First, all consumers in all seasons show an increase in electricity consumption between 3 pm and 4am, implying charging activities in these hours. There is also a decrease in electricity consumption in the morning hours from 8am to 10am, possibly due to the rebound in driving⁷.

⁷ Though we do not have the direct data on driving millage changes of EV households, to better support our claim of rebound effects, we compare the electric vehicle miles traveled (eVMT) per year for EVs with the average light duty vehicle miles traveled (VMT) in the US. According to the FHA (2020),

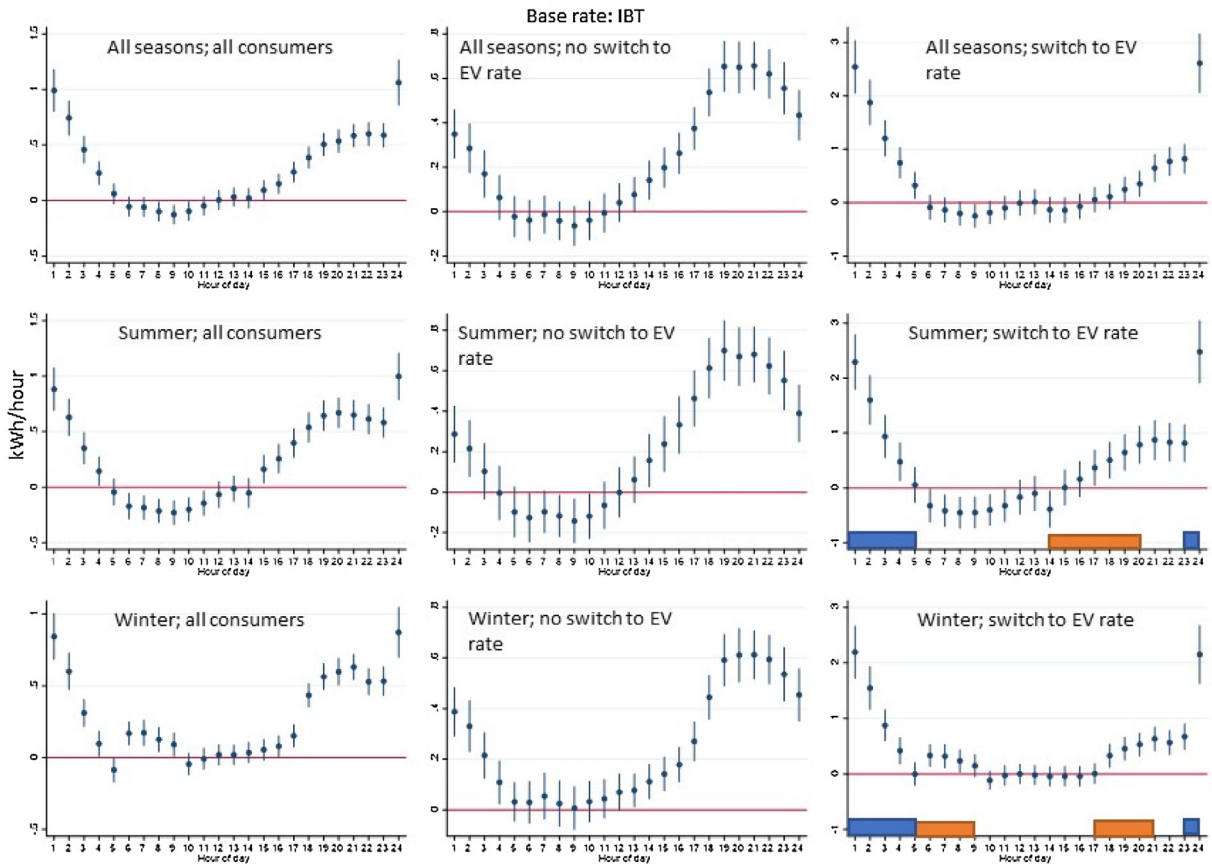


Fig. 3. Impact of EV in-home charging adoption on load profiles for consumers with increasing block rate as the base rate (IBT). Notes: The dots are the point estimates that measure the change in hourly electricity consumption due to EV charging. Vertical lines measure the 95 % confidence intervals. EV consumers can choose to switch to an EV rate which is a TOU price plan with super off-peak hours in all seasons from 11 pm–5 am. The summer months are May–October and the rest are winter months. The orange bars indicate the peak hours and the blue bars indicate the super off-peak hours for the EV rate. The number of each type of consumers in this figure: IBT control consumers– 1315, IBT EV consumers 876, IBT EV consumers staying with base rate–549, IBT EV consumers switching to EV rate – 327.

When consumers adopt in-home EV charging, it becomes cheaper to drive, resulting in more driving. This in turn makes EV drivers drive further away from home and contribute to the reduction of electricity consumption during these hours. Another explanation of the drop in electricity in certain hours could be that households are more aware of their electricity use and how it impacts their bills after purchasing an EV. Based on Fig. 3 for consumers with increasing block rate as the base rate, the reduction in electricity consumption in the morning hours happen for consumers both switching to EV TOU pricing and staying with the original rate, especially in the summer months. This implies that such an alternative behavioral response could happen for both non-TOU and TOU consumers.

US light duty vehicles were driven 11,467 miles in 2017 and 11,599 miles in 2019 on average. Some empirical studies have estimated the eVMT using survey data, electricity consumption data, and data loggers (Davis, 2019; Tal et al., 2021; Burlig et al., 2021). These studies are based on different data time windows, while the proportion of different models of EVs is changing fast and the eVMT by different models could vary a lot (Callaway and Fowlie, 2021). To be consistent with the time window in our sample (2014–2019), we compare the US light duty VMT with the estimated eVMT by the PHEV center, using data loggers from 2015 to 2020. The PHEV center tracks miles driven by 358 California EV drivers and estimates an eVMT of 12,900 miles per year on average, which is larger than the US average light duty VMT and indirectly supports our claim of the potential rebound effects in the paper. The PHEV center's estimate may have a limitation in its small and non-random sample, and the best data of eVMT is held by EV manufacturers themselves. Thus, to better support our claim, we also compare the light duty VMT with the estimate of eVMT using data provided by Tesla (Callaway and Fowlie, 2021). Since each Tesla EV is connected to the internet, Tesla can collect the data of eVMT from each individual vehicle. More importantly, Tesla occupies a large US EV market share, so using the eVMT of Tesla is meaningful. The sales of Tesla increase drastically since 2018 and then dominate the US EV market. In 2018, the sales of Tesla models (including Model 3, Model S, and Model X) account for 80% of national battery EV sales (AFDC, 2021). From 2014 to 2019, the total sales of Tesla account for 65%. Using the data provided by Tesla, Callaway and Fowlie estimate an eVMT of about 12,000 miles per year on average, which is a little higher than a typical light-duty vehicle in the US. Also, they find that the median eVMT of Tesla per year is larger than the median gas-powered car. To sum up, EV owners could drive more than typical light duty vehicles, particularly after 2018, in which Tesla models started to dominate the US EV market. Thus, more driving of EV owners could lead to decreased electricity consumption in certain hours, which is what we called rebound effects in this paper.

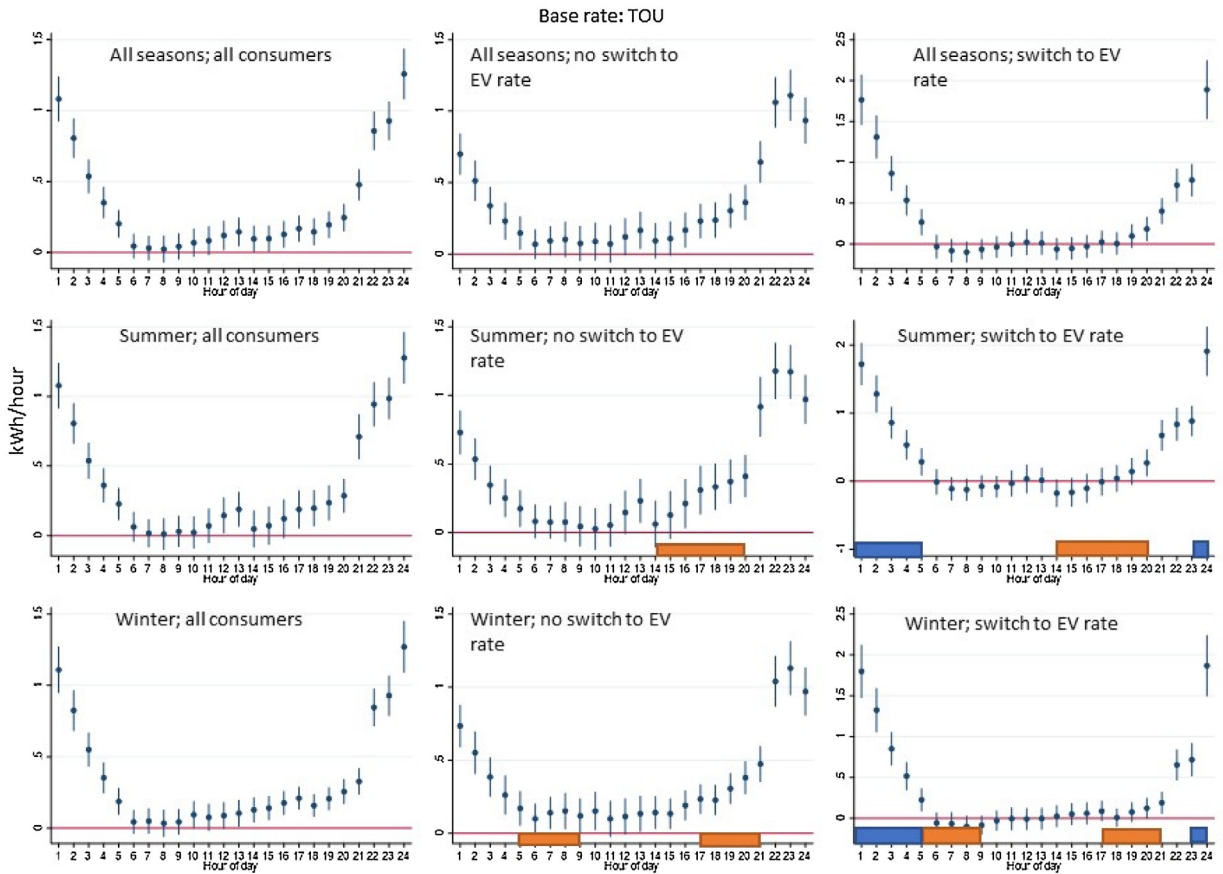


Fig. 4. Impact of EV in-home charging adoption on load profiles for consumers with TOU rate as the base rate. Notes: The dots are the point estimates that measure the change in hourly electricity consumption due to EV charging. Vertical lines measure the 95 % confidence intervals. The base rate TOU rate has peak hours 2–8 pm in summer months, and the peak hours 5–9 am & 5–9 pm in winter months. EV consumers can choose to switch to an EV rate which is a TOU price plan with super off-peak hours in all seasons from 11 pm–5 am. The orange bars indicate the peak hours and the blue bars indicate the super off-peak hours. The summer months are May–October and the rest are winter months. The number of each type of consumers in this figure: TOU control consumers–909, TOU EV consumers 813, TOU EV consumers staying with base rate–399, TOU EV consumers switching to EV rate–414.

We further breakdown the analysis by season and by whether EV consumers switch to the EV-specific rate. For consumers that stay with their base rate and do not switch to the EV rate, in the summer months, the increase in electricity consumption happens from 2 pm–2 am. The highest increase happens in the evening between 7–9 pm after people return home from work, on average about 0.665 kW h/hr/consumer in these hours, which can increase the pressure of the system during peak hours for the electric grid. System peak hours (the highest electricity demand for the whole year) tend to happen during summer months in early evenings and can impose significant pressure on the generating capacity and grid management in these hours. There is a reduction in consumption between 8 am–10 am, possibly due to rebound effects in driving as discussed earlier. For winter months, the increase in electricity happens for longer hours from noon–3 am. The highest increase also happens in the evening between 7–10 pm. There is no reduction in electricity during the winter months, indicating no rebound effects in driving during the winter.

For consumers that eventually switch to the EV rate, there is a much larger increase in electricity consumption from 11 pm–5 am, which coincides with the super off-peak hours of the EV rate. Similar to the consumers staying with the base rate, there is a rebound effect in driving for longer hours from 6 am to 11 am during summer months. There is also no rebound effects in driving during the winter for consumers switching to the EV rate.

• Impact for consumers with the base rate being TOU pricing

For consumers whose base rates are the TOU rate, the impact of EV in-home charging adoption is illustrated in Fig. 4 (Detailed coefficients and model results can be found in Supplementary Information Table S4). For all consumers in all seasons, on average there is an increase in electricity consumption between 12 pm–5 am, longer than the hours for consumers with the IBT base rate. There is no decrease in electricity consumption, indicating no rebound effects in driving.

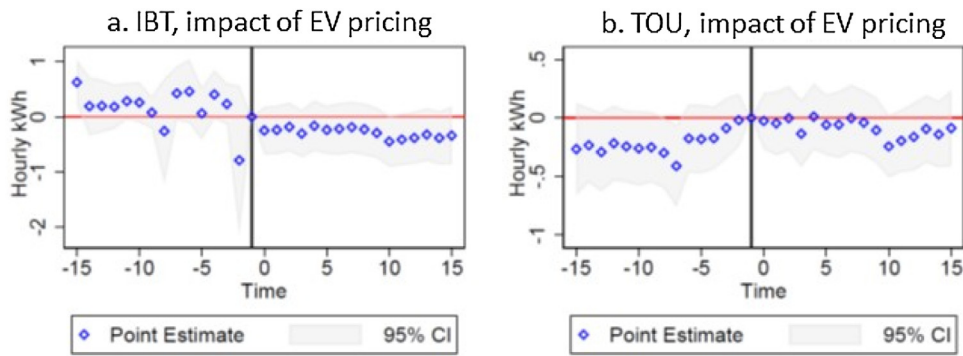


Fig. 5. Event study analysis of impact of switching to EV pricing. Notes: X-axis measures the number of weeks to EV pricing. Weeks prior to the pricing switch are indicated by -15 to 0 in the X-axis, and weeks after are indicated by 0 to 15. Y-axis measures the difference in the average hourly electricity consumption between the treatment and control groups; the difference is normalized to be zero at time -1. IBT and TOU indicate consumers with these two different base rates.

For consumers that stay with their base rate and do not switch to the EV rate, in summer months, the electricity consumption increases from 4pm–5am, even including the peak hours of the base rate TOU price plan (2–8 pm). The consumption also increases from 12 pm–1 pm, which may be due to efforts to avoid charging EVs during peak hours. The largest increase happens between 10–11 pm after the summer peak hours, on average about 1.18 kW h/hr/consumer in these hours, which may be due to increased charging after the peak hours end and before people go to bed. For winter months, the increase in electricity happens for longer hours in almost all hours. The increase in consumption is also much higher in late evening hours from 9 pm–midnight.

For consumers that eventually switch to the EV specific rate, there is a much larger increase in electricity consumption from 11 pm–5am, which coincides with the super off-peak hours of the EV rate. There is no increase in consumption in most peak hours except for 8–9 pm in the winter.

• Results using propensity score and coarsened exact matching

To further eliminate any potential systematic differences between EV and non-EV consumers, we conduct an analysis using statistical matching to make the EV consumers and the control consumers more comparable in terms of the pre-treatment electricity consumption profiles. We randomly assign a hypothetical EV charging date for each non-EV consumer. Then we calculate the average summer and winter electricity consumption for each EV and non-EV consumers, which we use as the two variables as well as zip-code in the matching process. The matching process makes the EV and non-EV consumers similar in terms of the pre-treatment electricity consumption levels. We use both propensity score matching (PSM, which gives us 561 treated and 1076 untreated consumers for IBT base rate and 619 treated and 768 untreated consumers for TOU base rate) and coarsened exact matching (CEM, which gives us 728 treated and 1311 untreated consumers for IBT base rate and 662 treated and 900 untreated consumers for TOU base rate). The event study analysis of the matched samples (Fig. 2 panels b, c, e, and f) show clear parallel trends in the pre-treatment periods, justifying the use of the DID method. Figs. S12 & 13 and Table S8 in the Supplementary Information show the matching results. The results on the electric grid impact are very similar to the main results using the randomly selected non-EV consumers as the control group, indicating the robustness of our main results.

4.2. Impact of EV-specific pricing on electric load profile

EV owners can opt into an EV pricing plan, which has significantly lower prices from 11 pm–5am year-round. There were usually a few months lag between the charging start dates and the dates of switching to the EV pricing. We utilize this time lag as a “pre-treatment period” to estimate the impact of pricing via DID, where the control group consists of EV homes that always stayed with the regular price plans. The treatment is switching to EV pricing in this analysis.

• Event study evidence

Again we first conduct an event study analysis to examine the difference in the post-charging electricity consumption between the two groups of EV consumers who switch to the EV rate and those who do not after starting in-home charging. Fig. 5 shows that there is no statistically significant difference between these two groups of consumers both before and after the treatment. This justifies the parallel trend assumption in consumption profiles. The insignificant change after the treatment in this analysis indicates that the EV pricing affects only intra-day shifting of EV charging but does not influence the aggregate amount of charging.

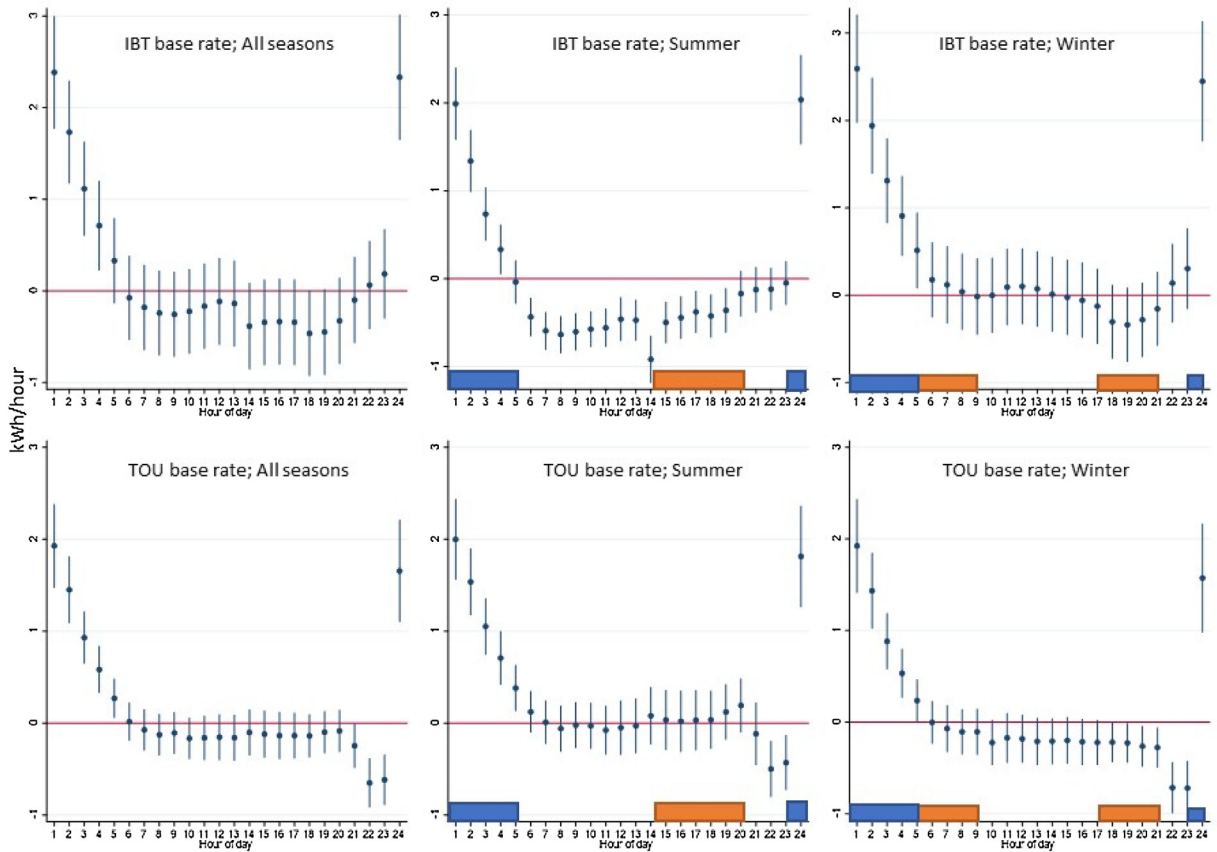


Fig. 6. Impact of switching to EV-specific electricity pricing on load profiles. Notes: The dots are the point estimates that measure the change in hourly electricity consumption due to EV pricing. Vertical lines measure the 95 % confidence intervals. The orange bars indicate the peak hours and the blue bars indicate the super off-peak hours. The summer months are May–October and the rest are winter months.

• Impact of switching to EV pricing

Results in Fig. 6 indicate that EV consumers are responding to electricity price signals (Detailed coefficients and model results can be found in Supplementary Information Table S5). We find that EV owners under the EV pricing plan increase their charging from 11 pm–5am which is exactly the super off-peak hours of the EV pricing, compared to EV owners who stay with their base price plans (more than 50 % of EV consumers).

Specifically, for EV consumers with the non-TOU IBT base rate, switching to EV pricing reduces electricity consumption not only during peak hours from 2–8 pm but also from 5am–2 pm in summer months. In winter months, there is no significant change in consumption throughout 24 h. For EV consumers with the TOU base rate, switching to EV pricing reduces electricity consumption between 9 pm and 11 pm but not before these hours in the evening in summer months. This implies that the EV pricing in this case may not serve the purpose of shaving the system peak demand from EV consumers during early evening hours. In winter months, switching to EV pricing reduces consumption by EV consumers with the TOU base rate during peak hours from 5 pm to 9 pm.⁸

Ideally to analyze the causal impact of retail electricity tariffs on EV in-home charging timing, researchers need to randomly allocate customers to different tariffs. In our setting, customers self-selected into the different tariffs. Customers that self-selected into the EV tariff could be the ones who were most likely to benefit from this tariff structure and were able to exploit these benefits by adjusting their consumption and charging patterns. This can lead to the over-estimation of the impact of EV pricing on the shifts of in-home charging timing. This endogeneity could also spill over into the estimated

⁸ In the winter month figure for consumers with IBT base rate, there is a strong increase in consumption in super off-peak hours but no reduction in other hours. We conduct a separate event study for the winter months of consumers with IBT base rate, and indeed the event study shows an average increase in overall electricity consumption due to switching to EV pricing. This, however, does not contradict with the original event study figure which shows no overall change in consumption if we include both winter and summer months. This is because in the summer months, there is an overall reduction in electricity consumption due to EV pricing. The different directions of the overall electricity consumption changes in summer versus winter months could be due to the fact that outdoor activities are more popular during winter months with mild temperature in Arizona.

treatment effects of EV charging on electricity consumption if those who can benefit the most from the EV tariff tend to purchase EVs and install in-home chargers. This spillover can lead to an over-estimation of the increase in electricity consumption due to EV charging. In our paper we tried to use several methods to correct for such biases. We first use fixed effects to control for unobserved confounding factors at consumer-level that do not change over time such as environmental and energy awareness and can influence the selection into EV pricing. We then use event study to check for parallel trend in electricity consumption behaviors in the pre-EV-pricing period between EV consumers who switched to EV pricing and those who did not.

4.3. Heterogeneity

We now examine whether the impact of EV in-home charging differs by type of charger and by weekend versus weekdays^{9, 10}.

• Results by types of charger

There are mainly two types of EV chargers for home use: level-1 charger and level-2 charger. A level-1 charger is plugged into a standard household outlet with 120-volt alternating-current (AC) at home, while a level-2 charger requires a 240-volt AC outlet, which is typically used for high-voltage household appliances, such as clothes driers, and installed in a garage in the U.S. Among the 684 EV consumers in our dataset who use a level-1 charger, 362 and 322 of them purchased electricity at the non-TOU base rate (IBT) and the TOU base rate respectively. Among the 1005 consumers¹¹ who use a level-2 charger, 514 had the non-TOU base rate, while 491 had the TOU base rate.

Fig. S2 in Supplementary Information compares the impact on load profiles by type of charger, by whether or not to switch to an EV rate, and by season for consumers who initially had the non-TOU base rate IBT. The left four graphs show that level-2 charger users who stayed on the non-TOU base rate (IBT) show fewer hours of charging because of the charger's higher capacity. In the right four graphs, for consumers who initially had the non-TOU base rate (IBT) but switched to the EV rate, the hours of charging do not differ significantly between level-1 and level-2 charger users. As expected, per-hour electricity consumption is higher for a level-2 charger. In particular, level-2 charger users increase electricity consumption dramatically from 11 pm–3am, taking advantage of the super off-peak rate. In terms of reduction in electricity consumption and thus rebound effects in driving, level-2 charger users who switched to the EV rate reduce electricity consumption from 6am to 11am in summer and from 1 pm to 5 pm in winter. There is no reduction of consumption by level-2 charger users who stayed with the base rate, perhaps because those who chose to switch to EV pricing are those who want to charge more and thus drive more.

Fig. S3 in Supplementary Information compares the impact on load profiles by type of charger, by whether or not to switch to an EV rate, and by season among consumers who initially had the TOU base rate. Among those who stayed with the TOU base rate, level-2 charger users have higher per-hour consumption, particularly from 10 pm to 3am. Similarly, among consumers who switched to the EV rate, level-2 charger users have higher per-hour consumption from 11 pm to 2am.

• By weekend/weekday

Fig. S4 in Supplementary Information shows the impact on load profiles by type of initial electricity rate and by season with a focus on differences between weekend and weekdays. It shows that consumers charge for more hours and more smoothly throughout the day during the weekend than on weekdays. In addition, in terms of the total amount of kWh charged, EV consumers charge more during weekdays compared to the weekend, possibly because people drive more during weekdays than on weekend (as illustrated by the average travel patterns by day of the week in Fig. S11 in the Supplementary Information).

⁹ Note that in the heterogeneity analysis and robustness checks, for the purpose of computation efficiency, we replace day-of-sample fixed effects with weekend indicator, holiday indicator, year-of sample fixed effects, and month-of-year fixed effects. Comparing our main results using day-of-sample fixed effects in Figs. 3–5 with the results using these new indicators and fixed effects in Figs. S14–16 in Supplementary Information, it shows that these two types of fixed effects generate very similar results.

¹⁰ We also examine the cluster of electricity consumption behaviors of EV consumers using a machine learning approach. Please refer to Supplementary Note-Machine learning clustering analysis for details.

¹¹ One might argue that since level 2 chargers are more expensive than level 1 chargers, it indicates that our sample of EV consumers might be a selected sample with wealthier EV consumers. However, as indicated in Supplementary Table S11, we compare the socio-demographics of our EV consumers with that of the EV consumers from the EIA RECS survey, which shows that our EV sample is similar to the RECS EV sample. This indicates that the selection to install level 2 chargers does not bias our sample.

4.4. Robustness checks

We conducted four robustness checks to help justify our main results. First, we include zip code-year fixed effects to control for any unobservable confounding factors that change over time at the zip code level (Fig. S7 in Supplementary Information). Such zip code-year fixed effects can control for factors that change at a community level over time, such as EV awareness campaigns or infrastructure development. These factors can influence consumers on both the decision to adopt EV charging and electricity consumption. Second, some EV users have only the post-treatment data in our dataset. We conduct a robustness check using only EV users that have records on both of the pre-treatment and post-treatment data in a strict DID analysis (Fig. S8 in Supplementary Information). Third, we conduct a robustness check using only the treatment group (those who eventually adopted EV chargers) to further eliminate any concerns about the systemic differences between the control and treatment groups (Fig. S9 in Supplementary Information). Lastly, we include a group-specific time trend (an interaction term between the treatment group indicator and the day-of-sample variable) to control for any potential differential trends in the pre-treatment period as well as to control for any time-variant unobservable differences between the EV charging and non-EV consumers (Fig. S10 in Supplementary Information), such as contemporaneous changes that can happen around the same time of adopting EV charging. For example, individuals might adopt other technologies around the same time as adopting in-home EV charging. They might also experience a change in housing retrofits or the number of households around the same time. All of these can impact electricity consumption profiles. The group-specific (control versus treatment groups) time trend can help control for these confounding factors. The results from these four robustness checks are consistent with our main results.

5. Grid impacts and environmental and private benefits

• Impact on the grid and role of pricing

In most regions such as in Arizona and California, the system peak hours can happen between 4–9 pm in summer, particularly in July and August. These are the hours of the highest electricity demand of the whole year. The electric power network infrastructure needs to be sized to meet this system peak demand. To a manager of power infrastructure, the increase in electricity consumption during the system peak hours is most important when analyzing the impact of EV on the electric grid. Focusing on the hours from 6 to 8 pm in summer, the average electricity demand of EV consumers in July and August before the adoption of EV charging is 4.8 kW and 5.4 kW for non-TOU base rate and TOU base rate consumers, respectively. Our results show that an average consumer on the non-TOU base rate can increase the load by 0.66 kW (or 14 % increase from pre-charging average consumption), while an average consumer on the TOU rate with peak hours 2–8 pm increase the load by 0.38 kW (or 7%). Switching to an EV rate with the super off-peak hours reduces the load by 0.21 kW from 6–8 pm for consumers who were previously on the increasing block rate, but has no impact for consumers who were previously on the TOU rate.

There are currently about 1000 increasing block rate EV-charging consumers and 800 TOU EV-charging consumers. This means that without an EV rate, these existing EV-charging consumers in total increase the system peak demand between 6–8 pm in the summer by 964 kW. If 10 % of SRP's total number of residential consumers (10 %* 690,200) install EV chargers, the increase in peak hours will equal approximately 36,964 kW for a single utility's system peak load, which is about the size of a small natural gas power plant.¹² A time-of-use rate that has peak hours during the system peak hours can reduce the increase in load from EV-charging.

The cost of this additional small natural gas generator is equal to about \$39.9 million (calculated from the per installed nameplate capacity cost: \$1,078/kW* 36,946 kW) (EIA, 2021, 55). Here we only focus on the impact on the cost of building generation capacity. However, the distribution network upgrade is also a major concern with coincidental EV charging. Future work needs to be done to quantify this important additional benefit of EV load shifting using empirical analysis.

• Environmental benefit

The electric grid is associated with environmental pollution because of burning fossil fuels, such as coal, oil, and natural gas. In this study, we conduct a back-of-the-envelope calculation of the environmental impact and consider major pollutants and GHG emissions, including CO₂, NO_x, SO₂, and PM (particulate matter). The amounts of emissions of these pollutants vary by hour of the day because the marginal fuel consumed to supply electricity is different. The change in electric load profiles due to EV charging will thus change environmental pollution from the electric grid. To calculate the environmental impact, we multiply the change in hourly electricity consumption estimated from our empirical analysis by the hourly marginal pollution emission factors from the electric grid. Using the hourly carbon and environmental marginal damage factors from (Holland et al., 2016), we estimate that average EV consumers, who use a level-1 or level-2 charger with the non-TOU base

¹² The assumed natural gas plant is a combined cycle single shaft technology, the use of which has steadily increased in the U.S. EIA does not provide the separate cost of a peaker unit versus a base unit.

rate, increase environmental damage from the electric grid by \$61/consumer/year; EV consumers with the TOU base rate increase environmental damage by \$72/consumer/year.

Then using the carbon and environmental damage estimated for gasoline-vehicle driving from (Holland et al., 2019; Parry et al., 2007), we calculate the damage from gasoline vehicles. Our estimated kWh charged per day can sustain driving for 20 miles on average for non-TOU EV consumers and 23 miles for TOU EV consumers (Table S6 in Supplementary Information provides details of calculation). If these miles were driven by a typical gasoline vehicle, it will generate environmental damage of about \$163/consumer/year and \$185/consumer/year, respectively. Therefore, the environmental benefit from in-home EV charging is $163 - 61 = \$101/\text{customer}/\text{year}$, and $185 - 72 = \$113/\text{customer}/\text{year}$, for non-TOU and TOU consumers, respectively. The detailed calculation of the environmental impact can be found in Table S6 in Supplementary Information.

• Private benefit

The saved expenditure on gasoline is the major private benefit of EV consumers with in-home chargers. We take the following three steps to conduct a back-of-the-envelope calculation of the saved expenditure. We first calculate the increase in electricity expenditure resulting from an increase in electricity consumption due to EV charging. Second, we estimate vehicle miles traveled (VMT) that could be driven with the amount of consumed electricity, and then convert this VMT to the amount of gasoline consumed. Then we calculate the difference in expenditure between driving on gasoline versus on electricity. The detailed calculation of the private benefits can be found in Table S7 in Supplementary Information. Our estimates of the private benefit of in-home EV charging are on average \$517/consumer/year for consumers with the non-TOU base rate and \$640/consumer/year for consumers with the TOU base rate.

• Compared to existing simulation studies

We now compare our empirically estimated changes in electric load profiles due to EV charging with those estimated from a few engineering studies. Two of the NREL simulation-based studies provide the charging profiles of various types of EV chargers including level-1 and level-2 home chargers, workplace chargers, and public chargers (McLaren et al., 2016; Wood et al., 2018). There are two major differences between our empirically estimated changes in electric load profiles and the results of residential charging by the NREL. First, the NREL studies indicate that residential charging starts around 6am and peaks between 7pm–10 pm. While our empirical results also show a peak charging hours from 7 pm to 10 pm for non-TOU consumers, the charging peaks around 10 pm–midnight for consumers on TOU pricing as the base rate. This difference tells us the importance of simulation-based studies to incorporate consumers' charging behavior changes in response to electricity price signals. Second, the NREL studies primarily focus on the amount of electricity charged by EVs but does not include electricity consumption for other purposes at home. However, the need for EV charging can further affect consumers' electricity consumption for other purposes. Our empirical results on the net electricity consumption show the reduction in electricity consumption for EV charging in certain hours possibly resulted from rebound effects in driving. No simulation-based studies currently consider such behavioral changes.

In addition to different EV charging timing, we also compare the magnitude, benefits, and costs of our estimated in-home EV charging' impact with those generated from the NREL simulation study by Muratori (2017). Detailed calculation is shown in Supplementary Tables S9 & 10. Muratori (2017) estimates an average electricity consumption increase of 12.3 kW h/day from EV in-home charging, while our estimate is only 7.1–7.6 kWh/day. The annual environmental benefit of the simulated in-home charging profile of an average EV household is \$196, compared to \$102 for IBT and \$113 for TOU consumers estimated from our empirical analysis. The simulated annual customers' private savings are \$909 for IBT and \$844 for TOU consumers, respectively, compared to \$516 and \$640 estimated from our empirical analysis. In terms of the system-wide costs, using the simulated EV in-home charging profile, the added demand during 6–8 pm assuming 10 % of SRP's EV penetration rate is equal to 63,997 kW, compared to 36,964 kW estimated using our empirical results. This comparison shows that simulation approach can over-estimate the environment benefits, system wide costs, and consumer private savings of in-home charging.¹³

• Link to the broader literature

Our study is relevant to the strand of energy economics and systems literature that examines the impacts of different electricity rates on consumers with distributed energy resources (DERs). The impacts on consumers' behaviors are assessed

¹³ The empirical study by Holland et al. (2016) estimated that on average in Phoenix Arizona, the environmental benefit of an EV relative to a 2014 Ford Focus gasoline car is equal to 0.74 cents per mile. According to Muratori (2017), an average EV household has 1.74 number of EVs. Based on our estimated increase in electricity consumption, an average EV household drives about 8,027 miles per year. Thus if we directly use the estimates from Holland et al., this will lead to an annual environmental benefit of \$103 ($0.74 \text{ cents} * 1.74 * 8,027$), which is of similar magnitude to and only slightly lower than our estimates of \$110–\$113. The difference is mainly due to the assumption of the cost of gasoline. Another engineering study (Rosato et al., 2017) uses the NYSERDA Wattplan calculator to estimate that the private fuel savings of a Nissan Leaf compared to a Honda Civic are \$275 per year, which is equivalent to \$478 per year at household level (assuming 1.74 EVs/household). This is lower than our estimates of private energy cost savings of \$516–\$640, which could be due to the assumptions of mileage driven and energy prices used in the engineering study.

either with tariffs defined exogenously (Ansarin et al., 2020; Avau et al., 2021; Backe et al., 2020; Gomes et al., 2021) or using equilibrium models in which grid tariffs are determined endogenously (Askeland et al., 2021; Hoarau and Perez, 2019; Schittekatte and Meeus, 2020). Hoarau and Perez (2018) analyze the interaction between tariff design and DERs with EVs to measure the most cost efficient and fairest configuration for heterogeneous agents. Askeland et al. (2021) highlight that an EV agent can spread the EV charging evenly throughout the day to minimize the agents' individual peak load regardless of the overall load situation. This can be problematic since the coincident peak can go up followed by a tariff increase. Schittekatte and Meeus (2020) point out that cost-reflective tariffs can benefit both prosumers who can invest in DERs and consumers who are not able to (Hildermeier et al., 2019) argue that customer education is key to attract new EV user groups. Mayol and Staropoli (2021) find that if adequate information about tariffs and behavior is provided, users usually choose more complex tariffs. Küfeoğlu et al. (2019) support the idea that energy utilities must offer consumers more options for TOU tariffs, not only allowing for greater demand-side management but also encouraging uptake of vehicle-to-grid (V2G) technology. King and Datta (2018) point out that submetering is a far less expensive option than the installation of a separate meter for the EV for the purpose of appropriate billing of EV consumers.

Our study is also related to a second strand of literature studying EV demand-side flexibility which raises attention to the challenges and opportunities expected during EV uptake. Knezović et al. (2017) provide a roadmap with key recommendations for supporting active EV involvement in grids to provide flexibility services such as investment deferral, load, and voltage services. Thompson and Perez (2020) discuss the value streams of numerous V2G services. Salah et al. (2015) argue that price incentives can help to exploit available load flexibility embedded in EV charging, whilst if ill-designed, they can lead to a significant increase of peak loads in times of low prices. Network investment deferral supported by EV flexibility in a context with renewable energy as explored by Hemmati and Mehrjerdi (2020), can contribute to an accessible cost-reflective tariff.

6. Conclusions and policy implications

The current literature has a critical gap, that is, the lack of empirical assessment of the impact of in-home EV charging on electric grids, as well as associated social and environmental impacts. Using a rich dataset with hourly smart meter data of 1600 EV consumers and a comparable number of non-EV consumers, the timing of EV charging adoption, and information of electricity pricing plan enrollment, we provide empirical evidence on the impact of in-home EV charging on residential electric load profiles and how such impact responds to various electricity price plans.

Our analysis has four key findings. First, using panel regression and difference-in-differences methods, we find that an average residential EV charging consumer can increase the electricity demand by 7–14 % during the system peak hours from 6 to 8 pm in summer. A 10 % residential penetration rate of a single utility's service territory implies that a new natural gas power plant is needed to meet the additional demand during the system peak hours. In other hours, EV consumers increase electricity in the afternoon, evening, and midnight, with charging most around midnight. Second, we find that EV consumers respond to electricity pricing signals by increasing charging during the super off-peak hours in an EV-specific time-of-use (TOU) pricing. EV consumers with the regular TOU pricing also behave differently, compared to EV consumers with the non-TOU pricing; TOU EV consumers charge more during their regular off-peak hours. Third, our empirical estimates of changes in electric load profiles due to EV charging are different from the charging profiles found in the previous simulation studies, highlighting the importance of empirical studies due to behavioral changes. One such behavioral change is rebound effects in driving which leads to a reduction in electricity usage in some hours of the day. Lastly, we estimate that the environmental benefit of in-home EV charging is \$101–113/consumer/year and the private benefit is \$517–640/consumer/year.

Our results have important implications for energy policymakers and electricity industry practitioners. First, our results show the potentially large impact on the electricity demand during system peak hours, which requires the expansion of the peak capacity of the electric infrastructure and better grid management in response to increasing penetration of in-home EV charging. Second, we show that in-home EV charging behaviors respond to electricity pricing. Our empirically-estimated response to pricing helps policymakers and utilities to adopt and evaluate pricing tools to help shift the EV charging load to off-peak hours from peak hours, to flatten the electric load curve, and to induce the highest social benefits of EVs. Third, our results show that it is important to provide empirical assessment instead of relying only on simulation studies because current simulation studies do not take into the effects of consumer behavioral changes, such as response to pricing or rebound effects in driving. Such deviations between predicted and actual behaviors imply potential adjustment of relevant policy interventions. Our paper illustrates the critical needs for more empirical assessments of EV in-home charging in broader geographical areas in the future.

Financial disclosure statement

There is financial disclosure applicable.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.reseneeco.2021.101275>.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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