Do EV Charging Stations Care about Electricity Rates?

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Abstract

This paper examines the relationship between electricity rate plans and EV charging station installations. I match the number of EV charging stations in a zip code area to commercial electricity tariffs of investor-owned utility companies in the United States from 2015 to 2022. Then, I use the local projection difference in differences method and the panel synthetic control method to estimate how newly introduced EV-related electricity tariffs, most of which designed to alleviate the burden of high demand charges, affected EV charging station entries. The result indicates that about 1 more charging port was installed after the EV-dedicated tariffs were introduced.

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1 Introduction

The transportation sector is widely recognized as one of the principal contributors to carbon dioxide (CO2) emissions. In 2022, the Environmental Protection Agency (EPA) reported that the transportation sector accounted for 35% of total CO2 emissions in the United States. In response to this environmental challenge, countries around the globe have initiated efforts to mitigate carbon emissions from transportation through the promotion of electric vehicle (EV) adoption. Nevertheless, these initiatives encounter numerous obstacles. A survey conducted by Consumer Reports in 2020[1] revealed that only 4% of a sample of 3,392 American adults expressed an intention to select an EV as their next vehicle. Conversely, 69% indicated that they do not plan to purchase an EV. Among the 96% of respondents not inclined to acquire an EV, 48% attributed their reluctance to the insufficient availability of public charging stations. Furthermore, 42% identified the limited driving range of EVs as a significant constraint, while 28% and 21% cited the lack of home charging options and prolonged charging times, respectively, as key barriers. In addition, Greene et al. (2020) estimates that California's public charging network in 2017 worth more than $6500 to a new BEV driver with a 100-mile range and home recharging. This implies people living in other states with less denser charging network are losing thousands of dollars. On top of the challenges posed by high upfront costs and insufficient knowledge about electric vehicles, the lack of a robust charging infrastructure remains a formidable impediment to widespread EV adoption.

There are two sets of federal, state, or local-level strategies aimed at promoting the adoption of EV charging stations and addressing concerns related to charging. The first set of initiatives directly subsidize fixed cost of installing EVSEs. The Biden-Harris administration proposed to build 500,000 EV charging stations nationwide by 2030. The National Electric Vehicle Infrastructure (NEVI) Formula Program is planned to fund states for installing charging stations. There are also state-level incentives for purchasing and installing charging devices[2]. You can check more municipality and utility-level rebates

[1] `https://advocacy.consumerreports.org/wp-content/uploads/2020/12/CR-National-EV-Survey-December-2020-2.pdf`

[2] Check `https://clippercreek.com/evse-rebates-and-tax-credits-by-state/`, visited on Feb

on the Alternative Fuel Data Center website. Besides monetary benefits, states like California, Oregon, and Washington have introduced building codes that require buildings to be EV-ready[3]. According to the Southwest Energy Efficiency Project (SWEEP), a building is EV-ready when electrical panel capacity meets a standard and a raceway with conduit that ends in a junction box or 240-volt charging outlet is installed. The second set of policies, which are less visible and are the focus of this paper, involves the introduction of new electricity tariffs specifically designed for public EV charging stations. States such as California, Illinois, and New York have mandated utility companies to create new electricity tariffs for EV charging stations. These new tariff structures are intended to replace traditional demand-based tariffs and alleviate the financial burdens faced by EV charging stations, particularly in relation to high demand charges. Have new electricity tariffs impacted different components of electricity bill a charging station owner would face? And have they affected entry decisions for electric vehicle charging stations? Answers to these questions may help boost EV charging station installations more efficiently.

This paper aims to understand how charging station entry decisions are affected by electricity rates in the U.S. from 2015 to 2022. To do so, I have constructed a dataset on utility pricing for EV charging, including EV-specific pricing plans that I manually collected from several sources. This tariff information is merged to charging profile data in order to measure monthly electricity bills. Finally, I match the electricity cost to EV charging station data, which is obtained from the Monthly Energy Review (MER).

The synthetic difference-in-differences method (SDID) and the local projection difference-in-differences method (LPDID) are used to estimate the effect of introducing electricity tariffs dedicated to EV charging stations. The SDID regression in zipcode-quarter level without any controls tells the introduction of EV-dedicated tariffs increases the number of level 2 charging ports by 2 units, and DF fast charging ports by 3 units. The LPDID regression is in valid for level 2 charging ports [How should I write this?] while the result

14th, 2023.

[3]Check `https://www.swenergy.org/transportation/electric-vehicles/building-codes`, visited on Feb 14th, 2023.

for DC fast charging stations is consistent with the SDID result. [Electricity Bill Result HERE]

This paper contributes to a growing literature in economics of EV charging stations. First, there is a strand of literature which tries to find the optimal charging station allocation. Liu et al. (2013) suggested a two-step screening method to site the optimal locations for EV charging stations and a mathematical model, which included operating costs, to identify the optimal size of charging stations. Ghamami et al. (2016) simulated the optimal location and level of charging capacity based on the fixed installation cost and walking cost. Their numerical results show drivers may abandon remote parking lots if walking cost is high. Cui et al. (2019) introduced a mathematical model incorporating voltage regulation cost, protection device upgrade cost, and distribution line expansion cost. Pal et al. (2021) constructed a mathematical model considering limited electricity distribution capacity. Kavianipour et al. (2021) finds the location and the capacity of charging stations that minimizes the cost of installing charging stations and the cost of time spent to wait and detour to charge electric vehicles. Their numerical study, which uses two cities in Michigan, implies the battery size of EVs does not play an important role in choosing the number of chargers needed, while the speed of chargers significantly reduced the time spent to charge and wait. Kavianipour et al. (2022) focused on the intercity road network of Michigan. This paper reports unlike the urban setting, the battery size affects the location of charging stations, while the speed of charging machines still determines the number of chargers and the time drivers have to spend in charging stations. Singh et al. (2022) develops regression models based on simulated optimal charging capacity to ease the computational burden. Second, there are a set of empirical literature on EV charging station installation. Li et al. (2017); Springel (2021) set up a model incorporating the chicken and egg property of EV charging stations and electric vehicle adoption and simulated how different subsidies would affect the number of EVs registered. Both papers show subsidizing charging stations is more cost effective than paying subsidies for EV purchases. (Li, 2019) used a similar model and simulated the effect of having more unified charging protocols on welfare. Lastly, this paper contributes to a set of literature that focuses on how electricity rate design affects its customers. Papers like Muratori et al. (2019); Borlaug et al. (2023) discuss how station utilization affects the profitability of charging stations given the existance of demand charges for grid-purchased electricity. Another set of papers investigated homeowners and renters reacting differently to price incentives (Borenstein and Bushnell, 2022; Davis, 2023), while others studied the impact of price scheme on electricity consumption patterns (Fitzpatrick et al., 2020; Mascherbauer et al., 2022). This study contributes to these broad literature by empirically studying the effect of electricity tariffs on station entry decisions.

2 What is going on in the US EV charging industry

[change this "summary" part] This section illustrates some details of the US charging station industry. The first part explains some definitions and facts about EV charging industry. The second subsection illustrates why and how regulatory bodies are taking action to encourage EV charging station installation. The last part describes how a typical commercial electricity bill is constructed using a sample bill from a utility company [NEED SOME MORE SENTENCES HERE].

2.1 (Tentative title) EV Charging Station Industry

Let's start with some definitions. First, charging stations draw electricity from power lines. It is electricity utility companies who manage distribution and transmission lines that deliver energy to charging stations. There are three categories of electricity utility companies regarding their ownership structures. investor-owned utility (IOU), publicly-owned utility (POU), and cooperative utility. According to a dataset named "U.S. Electric Utility Companies and Rates: Look-up by Zipcode (2021)", there are 143 IOUs in the United States by 2021. As Kathryne and Palmer explains the utility companies are operating in either regulated markets or deregulated markets. Utility companies in regulated markets are the sole generators and distributors of electricity in their territories. On the contrary, there are multiple load-serving entities who sell electricity to consumers and multiple generators who provide electricity to the load-serving entities. Even though the deregulation have brought competition to the retail and the wholeslae markets, there is only one utility company who delivers electricity to the customers.

Second, the Open Charge Point Interface (OCPI) defines the EV charging infrastructure hierarchy: station location, charging port, and connectors. A station location consists of one or multiple charging devices, called electric vehicle supply equipments (EVSEs). Each EVSE may have multiple connectors, or plugs. However the number of connectors may be different from the number of vehicles that could be charged simultaneously. The number of charging ports is defined to be the maximum number of vehicles that could be charged at the same time. Furthermore, charging ports are classified in three types by their different charging speeds: Level 1, Level 2, and DC fast charge. According to the U.S. Department of Tranportation[4] Level 1 ports are the slowest, they charge 2-5 miles of driving range per hour. As a result, it is mostly used in domestic settings. Level 2 ports provide much more electricity to a vehicle than Level 1 ports. This charge type is the most prevalent type in public charging stations, see Figure 2. Level 2 chargers could add 10-20 miles of driving range per hour. DC fast chargers, or Level 3 chargers are the fastest, and probably the most famous type. Compared to a typical 7.2kW output of level 2 chargers, DC fast chargers have power output up to 500kW. As this type of equipment drain much more electricity from the grid, DC fast chargers can charge electric range 180-240 miles per hour.

The number of charge ports has increased. As shown in Figure 2, Level 2 and DC fast charge ports constitutes most of public charging ports.

According to Arlt and Astier (2023) identifies 59% of level 2 charging stations listed in the AFDC dataset are co-located with other retail stores.

Lastly, there are three components of electricity bill an EV charging station faces: demand charge, energy charge, and fixed charge. Figure 4 is a sample electricity bill for a business owner who is a customer of PG&E, an investor-owned utility company in California. A detailed breakdown of the electricity bill is posted in part 17. You could

[4] `https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds`, accessed March 1st, 2025

check the three non-tax components. First, the customer charge or fixed charge is paid monthly per meter as long as a customer is connected to the grid. It is a fixed cost because it does not depend on how much electricity a customer uses. The second component is the demand charge, the most complicated one to explain. A customer pays the demand charge in kilowatts (kW), which measures the speed the customer draws electricity from the grid. The demand charge is paid to cover the cost of maintaining capacity. Regarding the water analogy, you will pay more if your maximum demand is high because your utility company must install larger pipes and more powerful pumps to supply water. According to PG&E, there are two kinds of demand charges: maximum demand charge and maximum peak-period demand charge. The maximum demand charge applies to the maximum demand, or the maximum amount of electricity used in a 15 or 30-minute window, at any time in a month. On the other hand, the maximum peak-period demand charge applies only to the maximum demand during the month's peak hours. If the utility company has partial-peak hours defined, then there will be a maximum partial-peak demand charge. The last component is the energy charge. Many residential users only pay for the energy charge. Like water, you pay for the total amount of electricity used, measured in kilowatt-hours (kWh).

Table 1: Example Definition of Time Periods

Summer (June 1 - September 30)		
Peak	4:00 p.m. - 9:00 p.m.	Every day, including weekends and holidays
Off Peak	All other Hours.	
Winter (October 1 - May 30)		
Peak	4:00 p.m. - 9:00 p.m.	Every day, including weekends and holidays
Super Off-Peak	9:00 a.m. - 2:00 p.m.	Every day in March, April and May, including weekends and holidays
Off Peak	All other Hours.	

Following two scenarios will help readers understand how the demand charge interacts

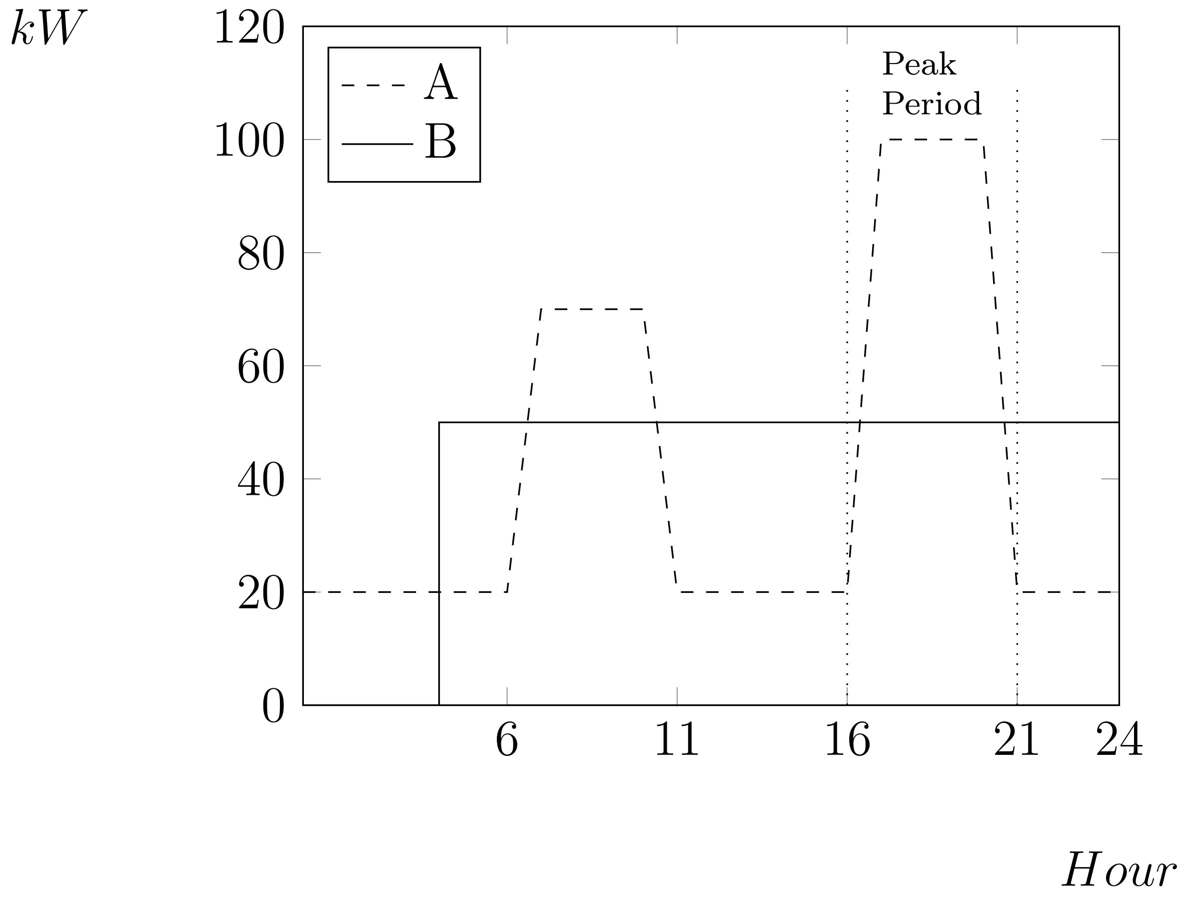


Figure 1: Electricity Usage Example

with different load profiles. Figure 1 illustrates electricity usage profile of scenario A and scenario B throughout a day in June. Assume that usage patterns are the same through out June. As shown in Table 1, June is one of summer months and there are peak hours and off peak hours. Further assume that customer charge is \$100 per meter per month, energy rate is \$0.1 per kWh, and the maximum peak period demand rate is \$20 per kW. Total electricity used in a day is 1000kWh in both scenarios. In scenario A, the maximum demand occurs on peak period, and is 100kW. On the other hand, scenario B has relatively flatter load profile. Its maximum demand is 50kW throughout the day. In this case, the total electricity charge for scenario A is $100 + 0.1 \times 1000 * 30 + 20 \times 100 = \$5100$ and that for scenario B is $100 + 0.1 \times 1000 * 30 + 20 \times 50 = \$4100$. In sum, even though two scenarios have the same amount of electricity used, the scenario with flatter load profile pays less electricity bill.

charging stations in different location venues experience different usage patterns. As a result, electricity load profiles they produce have different patterns. Figure 3 illustrates energy usage patterns of public level 2 ports. Green dotted lines represents mean usage among stations, while blue dots represents top 10% usage. Some locations have customers at night, for example, leisure destinations, parking garages, municipal buildings, hotels and transit facilities. Other locations mostly have their customers during day times. Furthermore, peak usages occur at different times. Stations near business offices or medical/educational campus have high usage at early afternoon, while other locations face smooth usage patterns.

2.2 States are Developing EV Dedicated Tariffs

Multiple states have recognized increasing charging demand. Some of them have promoted time of use (TOU) rate schedules, while others have introduced new tariffs designed for charging stations. For example, In March 2023, an EV Charging Rate Design Working Group established by the Pensilvenia Public Utility Commission published a set of recommendations for policy statements. Their third recommendation says the commission should request electric distribution companies to develop EV-specific rates by the end of 2023. The nineth recommendation encourages price signals for the benefit of ratepayers and the grid. The nineteenth recommendation requests utilities to propose an alternative to demand charges because the traditional form of demand charges hinder people from installing charging stations. Similarly, in 2021, Governor Hochul of New York established a public service law that requries the Public Service Commission to establish a commercial tariff that substitutes traditional demand charges, or relieve operating costs to enhance the deployment of public charging stations. Following this, Department of Public Service Staff submitted EV Phase-In Rate Solution. The proposed rate is a combination of TOU Energy rates and demand charge discounts based on load factors. This solution is expected to help diminish barriers to EV charging while stations have a higher than average kW demand relative to their kWh usage for charging since the EV chargers are not utilized as often, and stations are ramping-up their charging infrastructure.

Alongside the decisions made by state regulators, many investor-owned utilities are aiming to minimize the impact of demand charges, particularly during the initial period of the adoption. A report published by Synapse Energy summarizes some of them. Con Edison of New York offers a temporary reduction for electricity delivery charges while Pacific Power of Oregon temporarily discounts demand charges. Furthermore, Xcel Energy in Colorado and Southern California Edison in California introduced a new set of tariffs that eliminated demand charges and compensated the loss with increased energy charges. In addition to the report, PECO of Pensilvenia applies a fixed demand credit initially equal to 50% of DCFC nameplate capacity for 36 months. Its demand charge credit aims to encourage development of public DCFC charging stations by mitigating demand charges during early adoption period. ComEd which operates in Illinois offers its commercial and industrial customers with alternatives to traditional kW demand-based delivery rates.

3 Data

3.1 Data Description

EV Charging Ports. The Monthly Energy Review (MER) published by the EIA offers charging station information such as longitude, latitude, opening date, types of charging devices, etc, begining June 2015. The MER imports the raw data from the Alternative Fuels Data Center (AFDC) database on monthly basis. One strength of the MER dataset over the AFDC dataset is that it keeps the record of closed charging stations. Once a station closes, its information is deleted from the AFDC database. If a charging station operator like ChargePoint decides to renovate their stations and reopen them at the same they, one may find a huge number of charging stations entering the market at that date. Similarly, if mergers or changes in the ownership of stations occur, the AFDC dataset will record them as opening of new stations.

Electricity Tariffs. I compile information on electricity tariffs from multiple sources. Information about tariffs dedicated to commercial EV charging is manually collected, while information about the electricity rates in general are downloaded from the US Rate

Database (USRDB). In this version of the work, 24 investor owned utility companies are used, and 4 of them are treated. These utility companies were selected based on the census population they cover. The four treated utility companies are Pacific Gas & Electricity, Southern California Edison, Connecticut Power and Light, Florida Power and Light. A database published by the Edison Electric Institute (EEI) indicates there are more utility companies with EV-dedicated tariffs for business customers. The USRDB is a community driven database, therefore all data are uploaded by contributors. After being uploaded, each electricity rate plan is approved by staffs. I downloaded all tariff information including approved and not approved rate plans via API provided by the USRDB. The USRDB includes utility name, effective period of a electricity rates, and detailed rate plans. I merged zip code information using the utility-zip lookup table to generate utility-zip-quarter panel of electricity rate plans.

Electricity Load Profiles. The EVWATTS database offers electric vehicle supply equipment (EVSE) level electricity load profiles from 2019 to 2022. Information about charging sessions are recorded: when they started, when ended, how much electricity was provided, etc.

Zip Code Business Pattern. The fourth dataset is the Zip Code Business Pattern (ZBP). This dataset is used to control charging demand for two reasons. First, it is the electric vehicles on the road driving to work, shopping, or other tourist destinations that drive demand for public charging, not the electric vehicles registered in the zip code. The level of business activity will be correlated with the number of cars on the road, which will be correlated with the number of electric vehicles on the road. Thus, to capture trends in public charging demand, I control for zip-code level business activity. Second, I do not directly control the number of EVs registered in a zip code since EV ownership is co-determined with EV station entry. As illustrated in previous literature (Li et al., 2017; Springel, 2021), the full causal effect of electricity pricing on EV station entry operates, in part, via network effects on EV ownership.

Utility Territories. The last set of information I'm utilizing is the utility territory map maintained by the National Renewable Energy Laboratory (NREL).

This lookup table states which utility companies serve which zip codes. One problem is that multiple utility companies may provide electricity to different parts of one zip code area. In this case, the lookup table tells that all those utility companies cover the zip code. Therefore, I'm using utility-zip code pairs as unique identifiers.

3.2 Data Cleaning

This paper aims to understand how charging station entry decisions are affected by electricity rates in the U.S. from 2015 to 2022. To do so, I have constructed a dataset using five public datasets. First, I utilize the Monthly Energy Review (MER) to get the number of charging ports in a zip code area. The Energy Information Administration (EIA) pulled the information about EV charging stations from the Alternative Fuel Data Center (AFDC) and did their own cleaning to make the dataset. The original AFDC EV charging station location reports information such as the exact street address of a charging station, the number of EV Supply Equipment (EVSE), the number of charging ports, whether the station could be accessed by the public, etc. Second, data on electricity rate plans are downloaded from the U.S. Utility Rate Database (USRDB) via their application programming interface (API) and individual utility companies webpages. Energy charges, which are based on kWh usage; demand charges, which are based on kW maximum demand; and per meter fixed charges are collected. Third, I will use the American Community Survey (ACS) to control demographic information. Fourth, EVWATTS load profiles of different EVSEs downloaded from the Livewire Data Platform (LDP) are used. Lastly, I used a lookup table that links utility companies to zip codes generated by the National Renewable Energy Laboratory (NREL).

EV Charging Ports. The EIA added two new ID variables named "Location ID" and "Port ID". Stations in the AFDC dataset, which are considered to be in the same location, are assigned the same "Location ID". The AFDC assigned equipment IDs to stations, however one station may have multiple equipment IDs under certain circumstances, for example, some charging devices are networked but the others are not networked; some EVSEs in one station are publicly accessible while the access to the other units are restricted; or newly added charging devices might have received different equipment IDs. To construct "Location ID" the EIA used latitude and longitude pairings and equipment ID. As a result, a location ID could be a combination of multiple latitudes and longitudes parings as well as multiple equipment IDs. "Port ID", on the other hand, is created to distinguish charging machines with the same "Location ID" regarding their access types (public or private), network provider, charging speed level (Level 1, Level 2, or DC fast charger), and equipment ID.

I'm using the number of public Level 2 Port IDs in a zip code in the analysis because the number of charging locations experienced a break in series between December 2020 and January 2021 due to changes in the international standard, Open Charge Point Interface (OCPI).

Electricity Bills. To measure financial impact of the introduction of EV-dedicated tariffs, I calculate electricity bills a hypothetical charging station would face if it were located in each utility territories. First, Assuming a charging station has two identical EVSEs with the same load profiles, I could generate hypothetical charging stations that would be affected by changes in electricity rate schedules. Then, I calculate energy, demand, and fixed charges each hypothetical station would face under each electricity tariffs.

4 Empirical Methods and Results

I implement two empirical strategies to estimate the effect of the introduction of EV-dedicated tariffs on the number of charging ports: the synthetic control difference in differences.

4.1 Synthetic Control Difference in Differences

Synthetic control method (SC) (Abadie and Gardeazabal, 2003; Abadie et al., 2010) is becoming popular among researchers who try to analyze the effect of policy interventions when the variation is potentially endogenous. Abadie et al. (2010) shows that one could get an unbiased estimator of the treatment effect by constructing a synthetic control based on pre-treatment control and outcome variables. The synthetic control difference in differences method (Arkhangelsky et al., 2021) complements this method by allowing additive unit-level shifts ad large-panel inference. The basic SDID assumes a balanced panel with N units and T time periods. Further assume that the first N_{co} units are never treated group and the last $N_{tr} = N - N_{co}$ are affected by the policy after time T_{pre}. SDID resembles SC methods in a way that it assigns unit-wise weights on control groups that satisfy $\hat{\omega}_0 + \sum_{i=1}^{N_{co}} \hat{\omega}_i^{sdid} Y_{it} \approx N_{tr}^{-1} \sum_{i=N_{co}+1}^{N} Y_{it}$ for all $t = 1, \ldots, T_{pre}$ to constructs a synthetic control. On top of that SDID reweights time periods so that the following relation holds: $\hat{\lambda}_0 + \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} Y_{it} \approx T_{post}^{-1} \sum_{t=T_{pre}+1}^{T} Y_{it}$ for all $i = 1, \ldots, N_{co}$. Given weights on units, $\hat{\omega}_i^{sdid}$, and weights on time periods, $\hat{\lambda}_t^{sdid}$, the average causal effect, $\hat{\tau}^{sdid}$, is estimated:

$$\underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau\right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}. \tag{1}$$

The resulting estimate, $\hat{\tau}^{sdid}$, is

$$\hat{\tau}^{sdid} = \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} \hat{\delta}_i^{sdid} - \sum_{i=1}^{N_{co}} \hat{\omega}_i^{sdid} \hat{\delta}_i^{sdid} \quad \text{where} \quad \hat{\delta}_i^{sdid} = \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} - \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} Y_{it}. \tag{2}$$

This equation is alike that of difference in differences method where $\hat{\omega}_i^{did} = \frac{1}{N_{co}}$ and $\hat{\lambda}_t^{did} = \frac{1}{T_{pre}}$. Check Arkhangelsky et al. (2021) for more detailed explanation.

4.2 Local Projection Difference in Differences (LPDID)

The traditional DiD estimator could be biased twhen he introduction of EV-dedicated electricity tariffs had took place in different utility territories in different timings, due to "unclean" comparison between already treated groups and newly treated groups (Goodman-Bacon, 2021). To deal with this problem and to deal with potentially heterogeneous treatment effects, the local projection difference in differences estimation is used (Dube et al., 2023).

$$EVCP_{i,t+h} - EVCP_{i,t-1} =$$
$$\beta_h \Delta EVTariff_{i,t} + \Sigma_{k=1}^{p} \gamma_k^h EVCP_{i,k-j} + X_{it}\Gamma + \delta_t^h + \epsilon_{i,t}^h; \quad (3)$$

where $EVCP_{i,t}$ is the number of EV charging ports in a zipcode area i, in quarter t and $EVTariff_{i,k}$ is an indicator variable which equals 1 if an EV-dedicated tariff is introduced in time t. Lags of the number of charging ports are included ($p = 4$) to incorporate selection bias and installation bottleneck, that it takes 6 months to 1.5 years to install a charging station. Standard errors are clustered in utility level. Because the treatment is absorbing and there is a sufficient number of not-yet treated zipcode areas at all points in time, only not-yet treated are used as the control group:

$$\begin{cases} \text{newly treated,} & \Delta EVTariff_{it} = 1, \\ \text{or clean control,} & EVTariff_{i,t+h} = 0. \end{cases} \quad (4)$$

To further investigate what aspects of electricity bill had changed since the introduction of EV-dedicated tariffs, I'm utilizing the following estimation model:

$$ElecChargei, t + h - ElecChargei, t - 1 =$$
$$\beta_h \Delta EVTariff_{i,t} + X_{it}\Gamma + \delta_t^h + \epsilon_{i,t}^h; \quad (5)$$

where $ElecCharge \in [\text{Total Charge}, \text{Energy Charge}, \text{Demand Charge}, \text{Fixed Charge}]$. Unlike Eq. (3), lags of dependent variables are not included.

4.3 Results

In the current dataset, one utility company is always treated, Southern California Edison, three utility companies are treated at some point, Connecticut Light & Power, Florida Power & Light, and Pacific Gas & Electric, the other companies are never treated. Zipcode areas in these never treated utility territories form the donor pool. Then, the convex combination of zip code areas in the donor pool is constructed so that this synthetic control matches the treated counterpart in terms of values of EV charging ports predictors. Synthetic control difference in differences estimate indicates after the introduction of EV-dedicated tariffs, zipcodes in three treated utility territories had 0.98 more level 2 charging ports and 1.63 DC fast charging ports install on average. Figure Figs. 5–6 plot the quarterly estimates of the impacts of the introduction of EV charging tariffs, that is, the quarterly differences in the number of charging ports between real and synthetic zipcode areas. Figure 5 suggests that, on average, the enactment of new tariffs increased the number of charging ports in a zipcode area, and this effect increased in time to approximately 2 ports. Even more, the number of DC fast charging ports had constantly increased by more than 3 ports.

Zipcode areas in each treated utility territories experienced heterogeneous effects. Figs. 7–12 displays average EV charging ports for treated utility companies and its synthetic counterpart during the period 2015–2022. For all three utility territories, the average number of charging ports in each zip code areas closely follows the trajectory of this variable for the entire pre-treatment period. This is even noticeable given only few time periods were used to construct the synthetic controls. Fig. 7 and Fig. 10 show the estimated effect of the introduction of new EV charging tariffs in the CLP territories. The estimated treatment effect for level 2 ports is about -1.55, while the treatment effect for DC fast ports is 0.68. For the level 2 port case, a few quarters after the tariffs became effective, the two lines begin to diverge remarkably. While the synthetic CLP territory faced faster growth, the real CLP territory experienced similar growth rate. This negative effect of CLP's new set of tariffs could be due to their design. They were designed to be revenue neutral. They eliminated the demand rate, but tried to compensate the loss with higher energy rate. Unlike level 2 ports, DC fast ports benefited from the new tariffs. Compared to the synthetic counterpart, real CLP territory experienced faster growth. In contrast, PGE territory had average of 1.88 level 2 ports increased and 2.26 DC fast ports increased. Immediately after the introduction, the real trend diverges from the synthetic counterpart. The number of charging ports in the real PG&E territory increased substantially while the slop for the real the synthetic PG&E territory stayed the same. The magnitude of change is quite large. The increment of 1.88 level 2 ports is approximately 12.5% of the number of charging ports right before the enactment, while 2.26 DC fast ports is about 20-30% of the pre-treatment level. Lastly, Most of new ports were install in quarters 242 to 24x. FPL zip code areas had 0.05 level 2 ports and 0.42 DC fast ports were installed but these estimates are statistically insignificant. Two lines run mostly parallel to each other, but the real zipcode areas experience a change in the last part.

The LPDID estimation for level 2 ports which is depicted in Fig. 13 shows a bit concerning result. The pooled estimator, or the average value of the treatment effects is 1.137 and statistically significant in 5% level. However, though most pre-treatment estimates are statistically insignificant in 5% level, they are constantly positive. And the estimate for 6 quarters before the treatment is statistically significant. This may hint charging stations owners are postponing the installation when new tariffs are expected. Also, the parallel trend assumption may be in danger. However, DC fast ports reacted to the treatment. Fig. 14 shows that treated zip code areas faced constant growth in the number of charging ports after the introduction.

This result is driven by decrease in demand charges. As shown in Fig. 15 and Fig. 16, the total charge decreases a little bit after the introduction of EV-dedicated tariffs. This decrease in the total charge is driven by decrease in the demand charge.

5 Conclusion and Limitations

In order to have more EVs on the road, various regulatory bodies are subsidizing EV charging station installation. Besides direct subsidies on EVSEs, providing modified electricity tariffs has also been considered. This study investigates if the number of level 2 and DCFC ports had been increased since the introduction of tariffs specifically designed for EV charging stations. Findings from SDID and LPDID regressions indicate that about 1 more level 2 charging port was introduced on average in zip code areas with new electricity tariffs. However, the treatment effect is different across utility company territories. For example, zip code areas in PG&E territory experienced 1.88 level 2 ports increase while those in CPL territory faced 0.68 level 2 port decrease.

So far, the estimates are calculated without controlling for other variables. In the updated version, I'll include more control variables. Also, there are more than 100 utility companies throughout the U.S. Updates on tariff dataset is required.

Tables

Figures

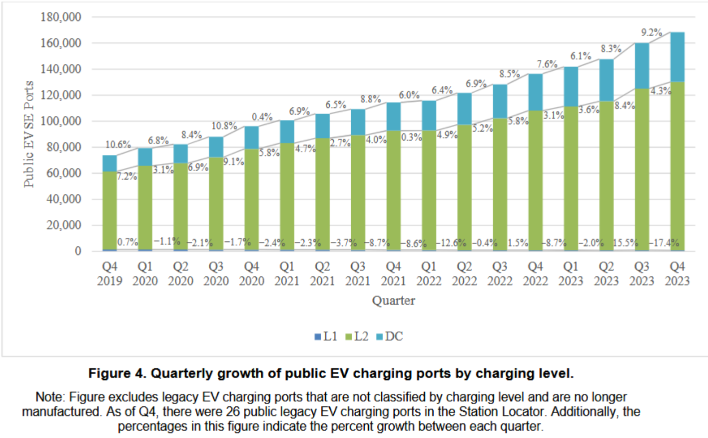


Figure 2: The number of charge ports by type

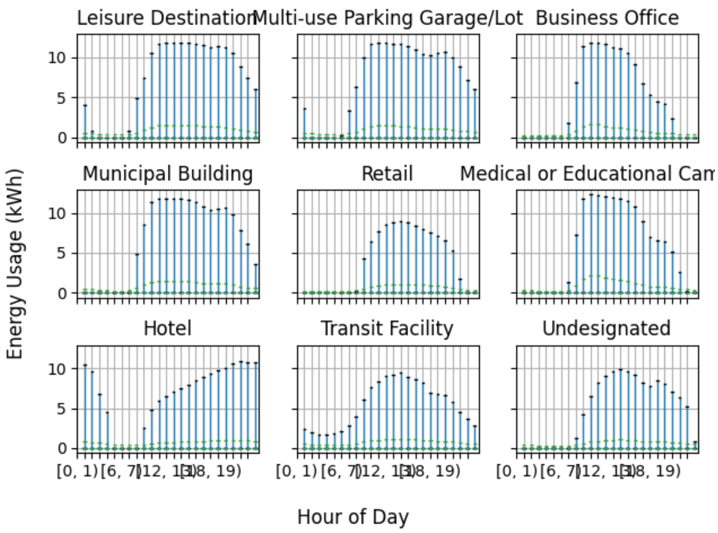


Figure 3: Load Profiles: Level 2

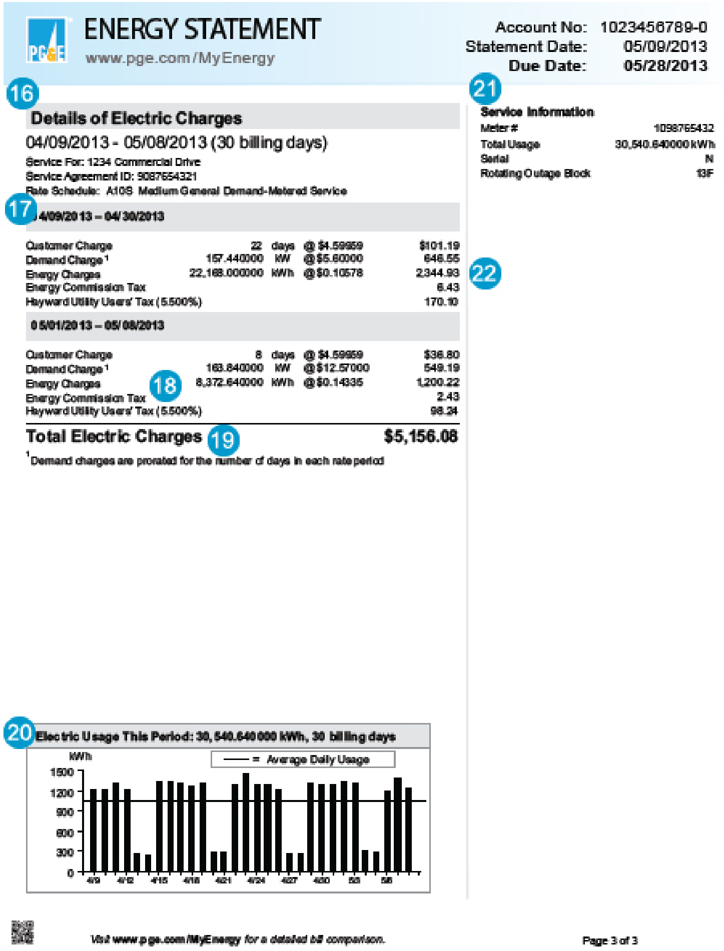


Figure 4: Sample Electricity Bill: PG&E

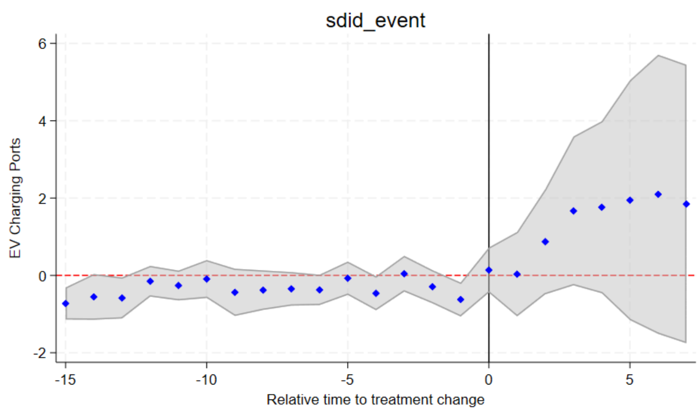


Figure 5: SDID Event Study, Level 2, All territories

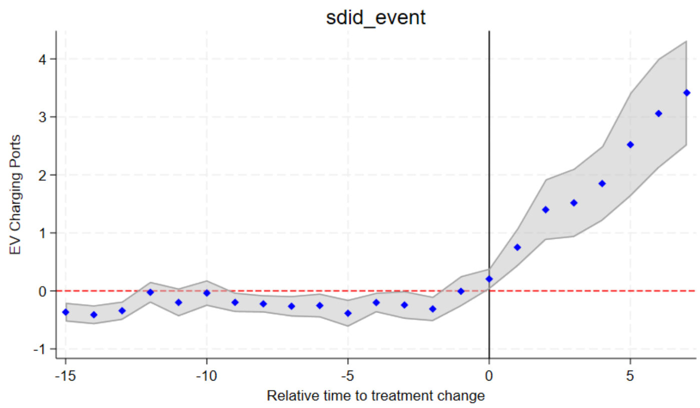


Figure 6: SDID Event Study, DC Fast, All territories

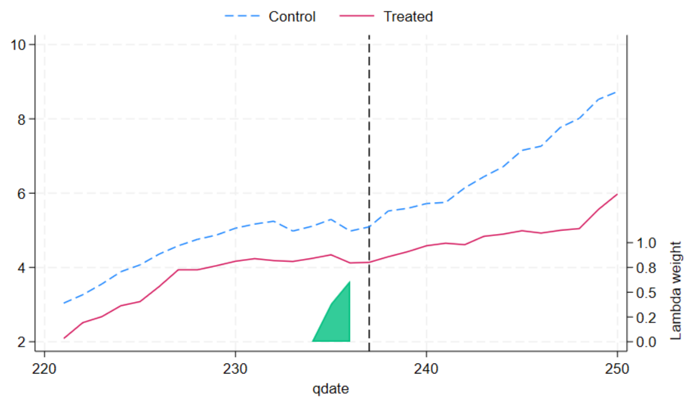


Figure 7: SDID, Level 2, Connecticut Light & Power

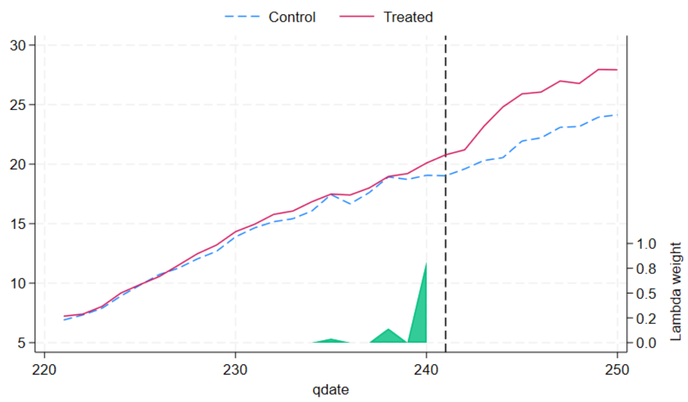


Figure 8: SDID, Level 2, Pacific Gas & Electric

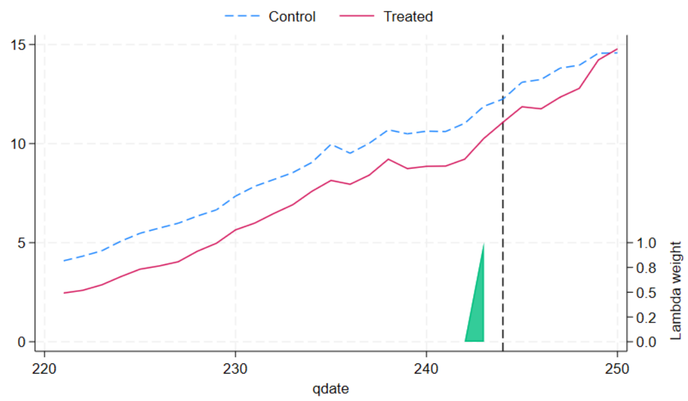


Figure 9: SDID, Level 2, Florida Power & Light

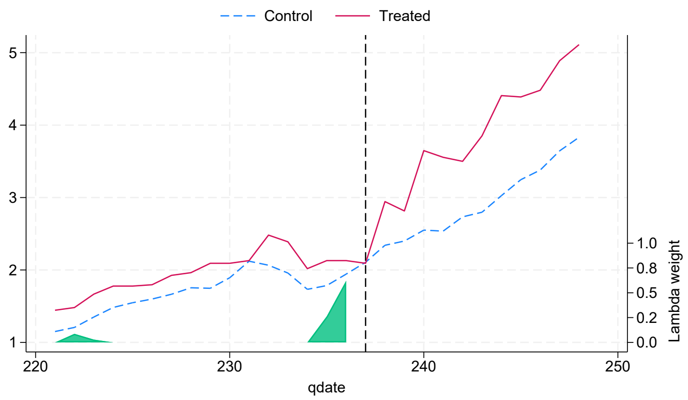


Figure 10: SDID, DC Fast, Connecticut Light & Power

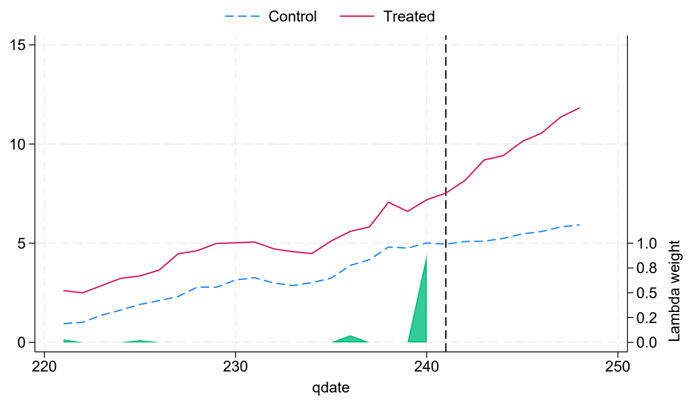


Figure 11: SDID, DC Fast, Pacific Gas & Electric

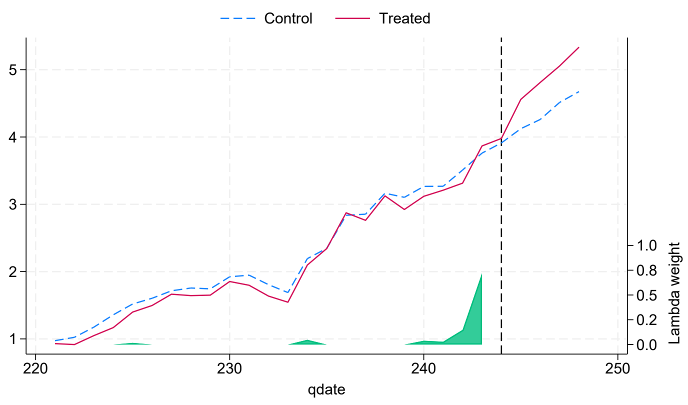


Figure 12: SDID, DC Fast, Florida Power & Light

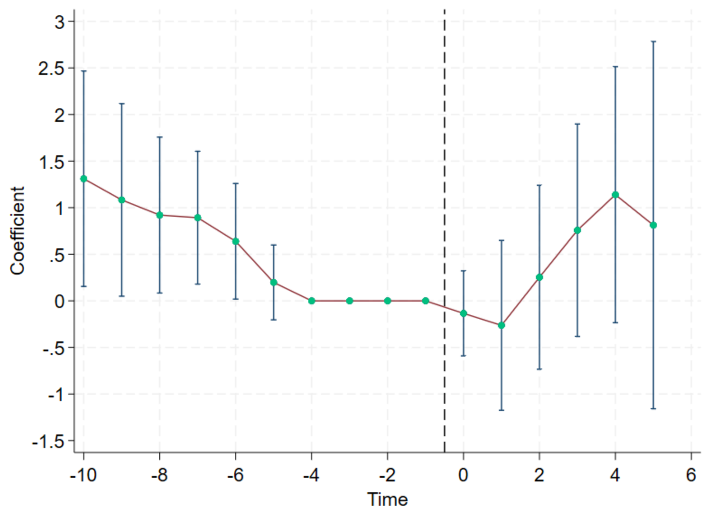


Figure 13: LPDID, Level 2, All Territories

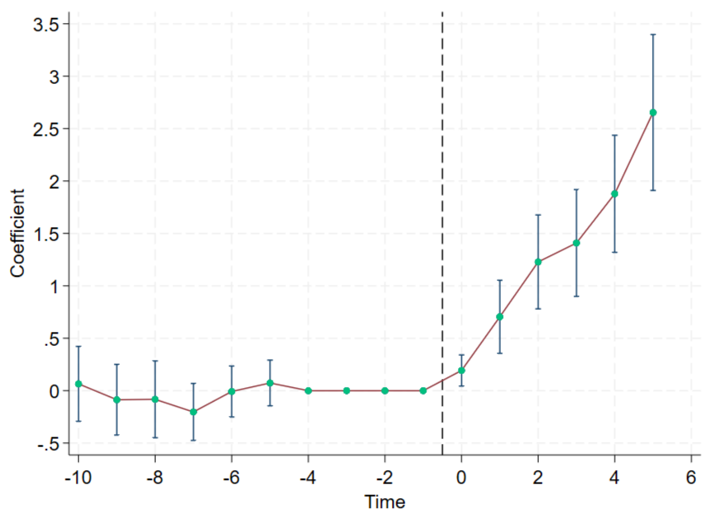
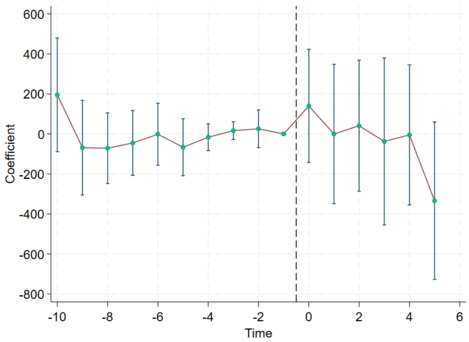
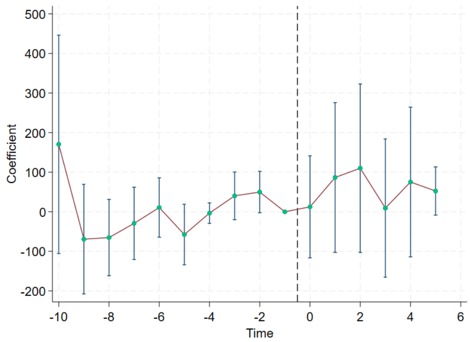


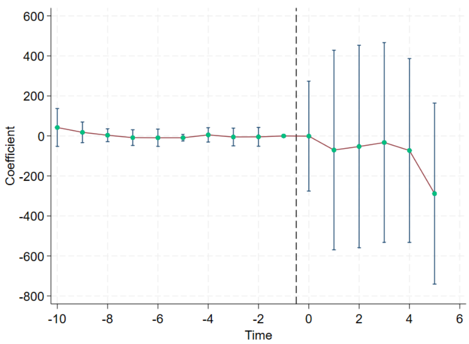
Figure 14: LPDID, DC Fast, All Territories



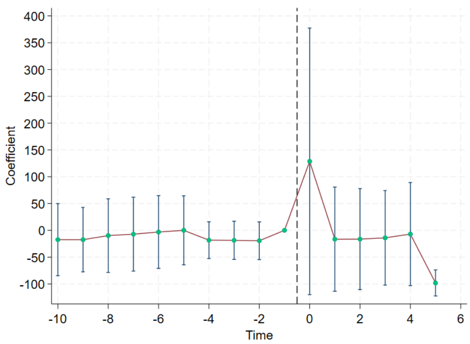
(a) Total Charge



(b) Energy Charge

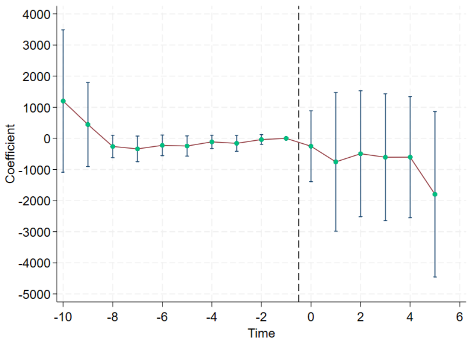


(c) Demand Charge

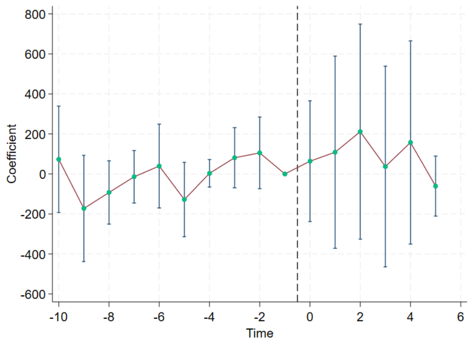


(d) Fixed Charge

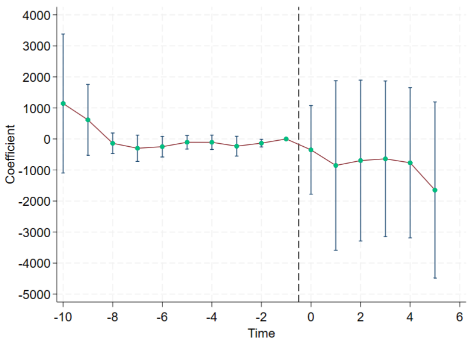
Figure 15: LPDID, Level 2, Electricity Bills



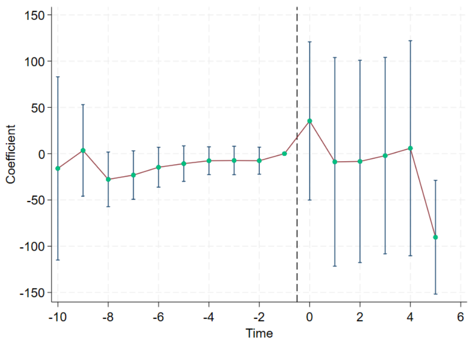
(a) Total Charge



(b) Energy Charge



(c) Demand Charge



(d) Fixed Charge

Figure 16: LPDID, DC Fast, Electricity Bills

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