Do EV Charging Stations Care about Electricity Rates?*

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Abstract

I study the effect of electricity prices on market entry of electric vehicle (EV) charging stations. I compile a novel dataset that links commercial electricity prices to charging stations across U.S. zip codes from 2015–2022. I translate complex pricing schedules into a standardized cost metric by constructing station-level load profiles based on observed charging sessions and calculating the resulting monthly electricity bills for those stations. Employing synthetic control and local projection difference-in-differences methods, I estimate the effects of new price schedules for EV charging stations—introduced to reduce high demand charges—on both station electricity costs and market entry. The results show that these schedules led to 35% increase the entry of DC fast charging ports, adding 0.920 more ports. This result is consistent with a reduction in total electricity charges, driven by significant decreases in energy and demand charges, 54% and 50%, respectively, underscoring the role of targeted rate design in accelerating EV infrastructure growth.

JEL Codes: Q4, Q5, R4, L94, R42

Keywords: EV Charging Infrastructure, Demand Charges, Electricity Rate Design, Market Entry

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1 Introduction

The transportation sector accounted for 35% of US carbon dioxide (CO2) emissions and 28% of total US greenhouse gas emissions in 2022 (Agency, 2024). 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] shows that only 4% of drivers definitely planned to purchase an EV for their next vehicle, with 48% of the remaining drivers attributing their reluctance to the insufficient availability of public charging stations. Meanwhile, limited driving range (42%), lack of home charging options (28%), and prolonged charging times (21%) were also identified as barriers, though less important. Greene et al. (2020) quantify the barrier, estimating that the convenience provided by California's extensive public charging network, relative to home charging, was worth more than $6500 to a new BEV driver, assuming a 100-mile range. These results imply that people in other states with less dense charging networks are losing thousands of dollars in value. 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 subsidizes the upfront cost of installing EV chargers. The Biden-Harris administration proposed to build 500,000 EV charging stations nationwide by 2030. The National Electric Vehicle Infrastructure (NEVI) Formula Program has funded states to install charging stations. There are also state-level incentives for purchasing and installing charging devices[2]. Besides monetary benefits, states like California, Oregon, and

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

[2] Check `https://afdc.energy.gov/laws/state`, visited on Apr 3rd, 2025.

Washington have introduced building codes that require buildings to be EV-ready[3][4]. The second set of policies, which are less visible and are the focus of this paper, involves the introduction of new electricity rate schedules designed explicitly for public EV charging stations. States such as California, Illinois, and New York have mandated utility companies to create new electricity rate schedules for EV charging stations. Traditional commercial electricity rate schedules often impose "demand charges" based on maximum electricity load (kW). Consequently, new rate structures are being introduced to replace these demand-based rate schedules and alleviate the financial burdens on EV charging stations. This paper addresses two research questions. First and foremost, have new electricity rat schedules impacted the entry decisions for electric vehicle charging stations? Second, have these new rate schedules affected the components of the electricity bill faced by charging station owners? The investigation of these questions provides policymakers with rationales for alternative policy options to boost EV adoption other than federal subsidies for electric vehicles and charging stations.

This paper combines three primary data files to empirically examine the effects of these newly proposed electricity rate schedules on the activity of EV charging stations in the United States from 2015 to 2022. First, I construct a novel dataset detailing commercial electricity pricing, including all dedicated rate schedules applicable to EV charging stations. This comprehensive information was manually gathered and verified from multiple utility and regulatory sources. This effort yields the first comprehensive database on rate schedules dedicated to EV charging stations, henceforth referred to as dedicated station rate schedules or simply station rate schedules. Second, I merge this rate schedule information with real world charging profile data to measure average monthly electricity bills that account for all three components of electricity rate schedules (energy, demand, and monthly charges). Finally, I match the electricity charges to data on the locations of EV charging stations over time from the Monthly Energy Review

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

[4]According to the Southwest Energy Efficiency Project (SWEEP), a building is EV-ready when its raceway has a conduit that ends in a junction box or 240-volt charging outlet and electrical panel capacity meets a standard.

(MER).

I then use the synthetic difference-in-differences (SDID) method and the local projection difference-in-differences (LPDID) method to estimate the effect of introducing electricity rates dedicated to EV charging stations on average prices and station entry at the zipcode-quarter level. I find using SDID that introducing dedicated station rates led to 63% decrease in demand charges faced by DC fast-charging stations and 121% increase in the demand charges faced by level 2 charging stations. These price changes, in turn, led to 0.920 additional DC fast-charging ports per zip code and 1.453 additional level-2 charging ports. These are about 20% and 8% of the average number of DC fast and level 2 charging ports in a zipcode area, respectively. The LPDID results confirm these findings for DC fast chargers almost exactly but appear to violate the common-trend assumption for level 2 charging ports.

This paper contributes to a growing literature on the economics of EV charging stations. First, there is a set of empirical literature on EV charging station installation. Li et al. (2017) and Springel (2021) set up models incorporating the chicken and egg property of EV charging stations and electric vehicle adoption and simulate how different subsidies would affect the number of EVs registered. Both papers show that subsidizing charging stations is more cost-effective than paying subsidies for EV purchases. Li et al. (2017) and Springel (2021) try to control for factors, such as public subsidies to build charging infrastructure, that affect fixed cost of entry. In addition, these papers use gasoline price as an instrumental variable to separate out the fixed costs of investment and the operating costs of the charger affecting the charging station entry decision. (Li, 2019) uses a similar two-sided model incorporating annual cost of charging station entry and simulates the effect of having a standardized charging protocol on consumer surplus, the number of charging locations and electric vehicles, finding $500 million consumer surplus increase, 2.8% fewer charging locations, and 20.8% more electric vehicle sales. This prior work estimates the capital cost and electricity cost components combined due to data constraints. However, they do not consider role of electricity rate schedules. I address these omissions by empirically studying the causal effect of dedicated station rate schedule reforms on station entry decisions. This analysis is grounded in an estimate of how these reforms affect the monthly cost of supplying electricity under observed charging scenarios. This contribution is made possible by compiling the most comprehensive dataset to date on dedicated station rate schedules, a fundamental constraint that prevented previous studies from integrating electricity costs into their models.

Second, a strand of literature in engineering studies the optimal charging station allocation. Papers like Ghamami et al. (2016), Cui et al. (2019), Pal et al. (2021), and Kavianipour et al. (2021) model optimal locations considering fixed installation costs. Ghamami et al. (2020) and Kavianipour et al. (2022) consider models with electricity provision costs, including but not limited to cost of installing a conduit from the transformer to the meter enclosure and protective equipment. Kavianipour et al. (2022) conduct a Michigan case study finding that faster chargers with fewer stations are able to meet charging demand. Other papers directly take electricity rates into consideration, but they do not utilize geographic variation. See for example Liu et al. (2011), Liu et al. (2013), and Huang and Kockelman (2020). Liu et al. (2011) and Liu et al. (2013) tested their models using hypothetical scenarios, Huang and Kockelman (2020) run a test on the Boston area. They find that charging stations avoid places with high land acquisition costs, that lower charging duration results in more charging stations, and that lower charging fee leads to more ports per station but fewer stations in total.

Finally, this paper contributes to a strand of literature that focuses on how electricity rate design affects customer behavior and infrastructure investment. While most prior work examining EVs and electricity rate schedules focuses exclusively on residential prices and household behavior, no empirical economic paper focuses on commercial charging stations. For example, a 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). Furthermore, a related body of econ-engineering literature studies interactions between electricity rate schedules in determining profitability of charging stations, given the existence of demand charges for grid-purchased electricity

(Muratori et al., 2019; Borlaug et al., 2023) or on the optimal location of new charging stations (Liu et al., 2011, 2013; Huang and Kockelman, 2020). However, these papers primarily rely on simulation or single-area case studies and do not empirically estimate the effect of rate design on market entry decisions. This study advances this literature by empirically examining the causal effect of electricity rate schedules on station entry decisions using nationwide data, providing real-world evidence of how profitability influences infrastructure investment.

Instead, I contribute to this literature by estimating how reforms to introduce dedicated station rates affect the monthly cost of supplying electricity under observed charging scenarios, along with the follow-on effects on station entry. I compile the most comprehensive dataset to date on dedicated station rate schedules, which prevented previous studies to utilize electricity costs in their models.

The rest of this paper proceeds as follows. Section 2 discusses the EV charging station industry. Section 3 describes data sources. Section 4 describes empirical methods for exploring the relationship between charging station entry and electricity costs. Section 5 reports results and discusses potential mechanism beneath them. Finally, section 6 concludes. By comparing utility companies across the United States. As a result, I can directly link how station profitability affects charging station entry.

2 Market structure and the demand charge barrier in EV charging

This section discusses some details of the U.S. charging station industry. The first part explains some definitions and facts about the 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.

2.1 EV Charging Station Industry

This subsection focuses on providing definitions related to EV charging. First, charging stations draw electricity from power lines. Electricity utility companies manage distribution and transmission lines that deliver energy to charging stations. There are three categories of electricity utility companies in 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 144 IOUs in the United States by 2021. As explained by Kathryne and Palmer (2020), utility companies are operating in either regulated or deregulated markets. Utility companies in regulated markets are the sole generators and distributors of electricity in their territories. On the contrary, multiple load-serving entities sell electricity to consumers, and multiple generators provide electricity to the load-serving entities. Even though the deregulation has brought competition to the retail and wholesale markets, only one utility company physically delivers electricity to the customers.

Second, the Open Charge Point Interface (OCPI), a standardization protocol that ensures compatibility among different charging networks, 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 equipment, hereinafter EV charger. Each EV charger may have multiple connectors or plugs. The number of connectors may differ from the number of vehicles that can be charged simultaneously. The definition of a charging port is the maximum number of vehicles that an EV charger could charge at the same time. Furthermore, charging ports are classified into three types based on their different charging speeds: Level 1, Level 2, and DC fast charge. According to the U.S. Department of Tranportation[5] Level 1 ports are the slowest, they charge 2-5 miles of driving range per hour. As a result, level 1 ports are only suitable for domestic usage. Level 2 ports provide much more electricity to a vehicle than Level 1 ports. This charge type is the most prevalent in public charging stations; see Figure 15. Level 2 chargers could add 10-20 miles of driving range per hour. DC fast or Level 3 chargers

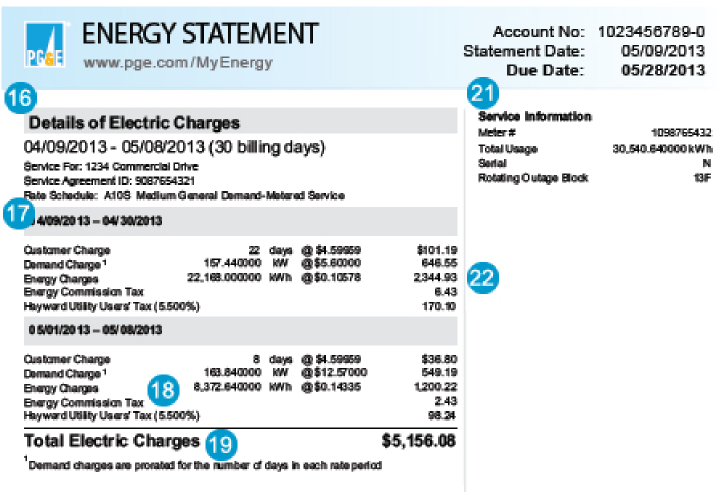
[5] `https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds`, accessed March 1st, 2025

are the fastest and probably the most famous type. Compared to a typical 7.2kW output of level 2 chargers, DC fast chargers have a power output of up to 500kW. As this type of equipment draws much more electricity from the grid, DC fast chargers can charge an electric range of 180-240 miles per hour.

The number of charging ports has steadily increased since 2019. As shown in Figure 15, Level 2 and DC fast charge ports constitute most public charging ports.

Lastly, an EV charging station faces an electricity bill with three components: demand charge, energy charge, and fixed charge. First, the customer 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, which is the most complicated one to explain. The customer pays the demand charge in kilowatts (kW), which measures the speed at which the customer draws electricity from the grid. The demand charge is paid to cover the cost of maintaining capacity. Using the water delivery as an analogy, the customer will pay more if the maximum demand is high because its utility company must install larger pipes and more powerful pumps to supply water. The last component is the energy charge. Many residential users only pay for the energy charge. Like water, the customer pays for the total electricity used, measured in kilowatt-hours (kWh).

Figure 1: Sample Electricity Bill: PG&E



ENERGY STATEMENT

www.pge.com/MyEnergy

Account No: 1023456789-0
Statement Date: 05/09/2013
Due Date: 05/28/2013

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Details of Electric Charges

04/09/2013 - 05/08/2013 (30 billing days)

Service For: 1234 Commercial Drive
Service Agreement ID: 9087654321
Rate Schedule: A10S Medium General Demand-Metered Service

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04/09/2013 – 04/30/2013

Customer Charge	22	days	@ $4.59959	$101.19
Demand Charge [1]	157.440000	kW	@ $5.60000	646.55
Energy Charges	22,168.000000	kWh	@ $0.10578	2,344.93
Energy Commission Tax				6.43
Hayward Utility Users' Tax (5.500%)				170.10

05/01/2013 – 05/08/2013

Customer Charge	8	days	@ $4.59959	$36.80
Demand Charge [1]	163.840000	kW	@ $12.57000	549.19
Energy Charges	8,372.640000	kWh	@ $0.14335	1,200.22
Energy Commission Tax				2.43
Hayward Utility Users' Tax (5.500%)				98.24

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Total Electric Charges 19 **$5,156.08**

[1] Demand charges are prorated for the number of days in each rate period

21

Service Information

Meter #	1098765432
Total Usage	30,540.640000 kWh
Serial	N
Rotating Outage Block	13F

22

Note: Section 17 shows the electricity bill a commercial customer would face for 30 billing days. There are three components: customer charge (or fixed charge), demand charge, and energy charge.

Figure 1 is a sample electricity bill for a business owner who is a customer of PG&E, an investor-owned utility company in California. Part 17 presents a detailed breakdown of the electricity bill. In part 17, there are three non-tax components.

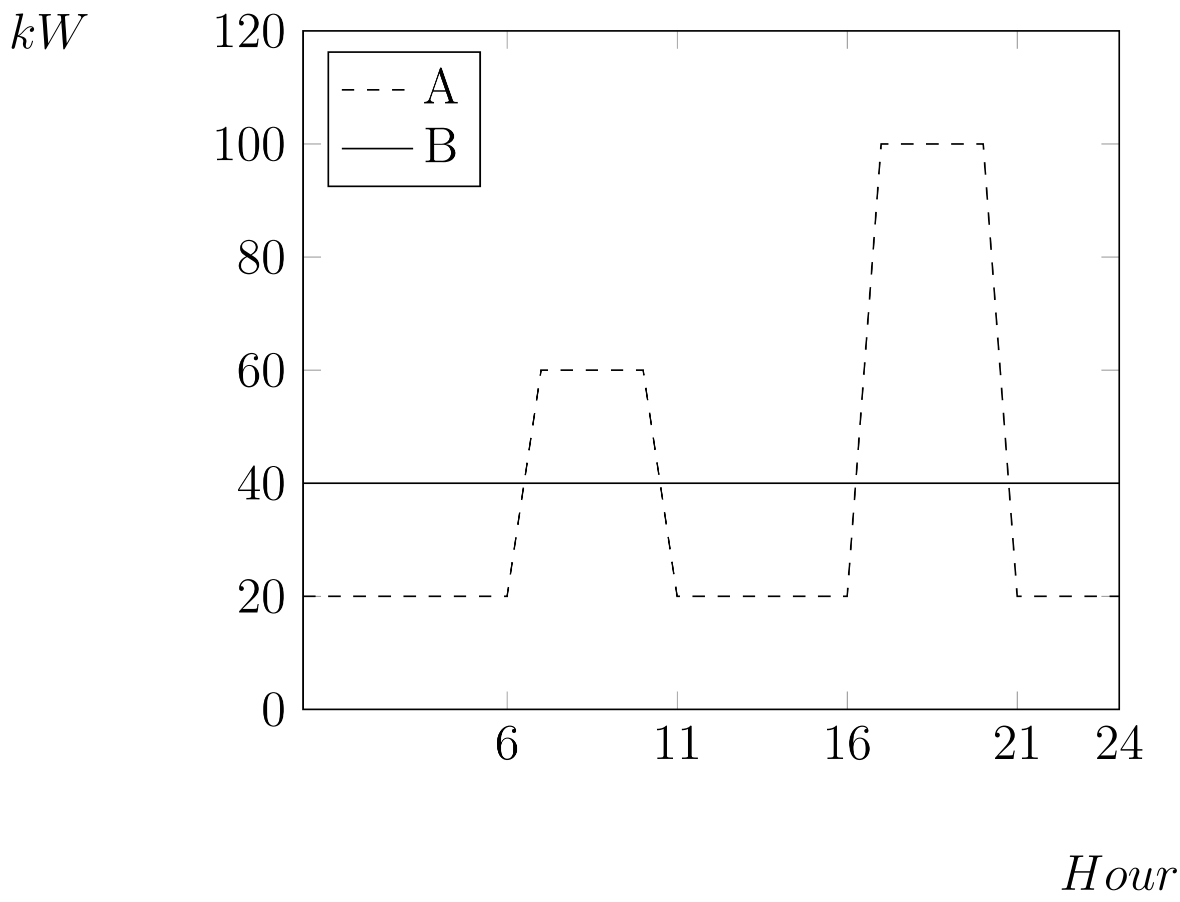


Figure 2: Peaky Usage vs. Flat Usage: Load Profiles

Note: The dashed line shows Customer A's electricity usage, with a peakier load profile typical of EV charging stations. The solid line shows Customer B's flatter usage pattern, representative of traditional office buildings. Both customers use the same amount of electricity, 960 kWh. Customer A's peak demand is 100 kW, and Customer B's peak demand is 40 kW.

The following example of two customers will help readers understand how the demand charge interacts with different load profiles. Figure 2 illustrates the electricity usage profile of customer A and customer B throughout a day. Assume that usage patterns are the same for 30 days, or for a month. Further assume that the two customers face electricity rate schedule as shown in Table 1. Specifically, the customer charge is $100 per meter per month, the energy rate is $0.1 per kWh, and the maximum demand rate is $20 per kW. Both customers use the same amount of electricity in a day, 960 kWh. For customer A, the maximum demand occurs between 5 pm and 8 pm, and is 100 kW. On the other hand, customer B has a flatter load profile. The station's maximum demand is 40kW throughout the day. In this case, the total electricity charge for customer A is $100 + 0.1 \times 960 * 30 + 10 \times 100 = \$3980$, and that for customer B is $100 + 0.1 \times 960 * 30 + 10 \times 40 = \$3380$. In sum, even though the two customers have the same amount of electricity used, the electricity bill for the customer with a flatter load profile is $600 less. The comparison is summarized in Table 1. Note that time-varying electricity prices ($/kWh) or demand charges ($/kW) that depend on time of day would lead to further variation in electricity bills based on differences in load profiles.

Table 1: Peaky Usage vs. Flat Usage: Electricity Bills

	Rates	Load Profile A		Load Profile B	
		Usage	Total	Usage	
Energy Charge	$0.1/kWh	28800 kWh	$2880	28800 kWh	$2880
Maximum Demand Charge	$10/kW	100 kW	$1000	40 kW	$400
Fixed Charge	$100/month	1 month	$100	1 month	$100
Total			$3980		$3380

Note: The table compares electricity usages and electricity bills of Customer A and B, assuming they maintain the same load profiles for 30 days. Because Customer A has peaky demand, it pays $600 more demand charge.

Compared to traditional commercial customers, such as large office buildings or retail stores, EV charging stations have more peaky load profiles like customer A. Between charging stations equipped with level 2 charging ports and those with DC fast charging ports, DC fast charging ports will incur more peaky load profile. In sum, EV charging stations will face higher electricity bill due to demand charge compared to other commercial users, and the demand charges will act as a barrier to DC fast charging stations, in particular.

Charging stations in different location venues experience different usage patterns. As a result, the electricity load profiles they produce have different patterns. Figure 3 illustrates energy usage patterns of public level 2 ports using EVWATTS data. Green dotted lines represent mean usage among stations, while blue dots represent the top 10% usage. Some locations have customers at night, such as leisure destinations, parking garages, municipal buildings, hotels, and transit facilities. Other locations mostly have their customers during the day. Furthermore, peak usages occur at different times. Stations near business offices or medical/educational campuses have high usage in the early afternoon, while other locations face smooth usage patterns. As shown above, different usage patterns will interact with complex rate structures to generate wide variation in monthly electricity bills.

2.2 States are Developing Dedicated Rate Schedules for EV Charging Stations

Multiple states have recognized increasing charging demand. Some have promoted time of use (TOU) rate schedules, while others have introduced new rate schedules designed for charging stations. For example, In March 2023, an EV Charging Rate Design Working Group established by the Pennsylvania 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 ninth recommendation encourages price signals to benefit ratepayers and the grid. The nineteenth recommendation requests utilities to propose an alternative to demand charges because the traditional demand charges hinder people from installing charging stations. Similarly, in 2021, Governor Hochul of New York established a public service law that requires the Public Service Commission to establish a commercial rate schedule that substitutes traditional demand charges or relieves operating costs to enhance the deployment of public charging stations. The Department of Public Service Staff submitted the EV Phase-In Rate Solution. The proposed rate combines TOU Energy rates and demand charge discounts based on load factors. This solution is expected to help diminish barriers to EV charging. At the same time, charging stations often 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 aim to minimize the impact of demand charges, particularly during the initial adoption period.

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 rate schedules that eliminated demand charges and compensated the loss with increased energy charges. In addition to the report, PECO of Pennsylvania applies for a fixed demand credit initially equal to 50% of kW nameplate capacity for 36 months for DC fast charging stations. Its demand charge credit aims to encourage the development of public DC fast charging stations by mitigating demand charges during the early adoption period. ComEd, which operates in Illinois, offers its commercial and industrial customers alternatives to traditional kW demand-based delivery rates.

3 Data

This study analyzes the entry decisions of public EV charging stations by constructing a comprehensive panel dataset covering the service territories of 70 major U.S. investor-owned utilities (IOUs) from 2015Q2 to 2022Q1. The dataset is built by integrating six public data sources. The primary dependent variable, the quarterly count of charging ports at the zip-code level, is derived from the Monthly Energy Review (MER). The key independent variables, which capture the complex structure of commercial electricity rates, are sourced from the U.S. Utility Rate Database (USRDB) and supplemented by manual collection. To simulate station-level electricity costs, I utilize representative charging load profiles from the EVWATTS project. A set of control variables for local demographics, economic activity, and state-level policies are incorporated from the American Community Survey (ACS), Zip Code Business Patterns (ZBP), and the Database of State Incentives for Renewables & Efficiency (DSIRE), respectively. Finally, a lookup table from the National Renewable Energy Laboratory (NREL) is used to map zip codes to their corresponding utility service territories.

3.1 Data Description

EV Charging Ports. This study measures charging infrastructure using historical data from the U.S. Energy Information Administration's (EIA) Monthly Energy Review (MER), which began in June 2015. While the MER aggregates data from the Alternative Fuels Data Center (AFDC), its key advantage for panel analysis is the retention of records for closed stations, providing a more stable historical account.[6]

In MER, charging stations can be identified using Location IDs, while Port IDs add operational characteristics of charging equipment to Location IDs. However, I measure entry via the total number of public charging ports in a zip code, rather than Location IDs or the Port ID count itself, for two critical reasons.[7] First, both Location IDs and Port IDs are inherently unstable measures of the charging network's size. The total number of charging locations based on Location IDs experienced a severe break in the series between December 2020 and January 2021 due to an AFDC data transition to the OCPI protocol. This discontinuity resulted in locations previously counted as one station being artificially split into multiple IDs, inflating the station count. Port ID, by its setup, also suffers the same problem. Second, the total number of ports is the only measure that consistently reflects actual charging service capacity. Unlike Location IDs (which only identify a site) or the Port ID count (which reflects the count of equipment types), the aggregated count of individual ports directly captures the capacity available to drivers. Crucially, this physical count was maintained and remained stable even when the underlying ID logic changed during the 2020–2021 discontinuity. Therefore, I use the number of ports as the dependent variable because it accurately reflects the change in charging service capacity added to the market without suffering from the measurement error introduced by the OCPI transition.

[6] MER imports the raw data from the Alternative Fuels Data Center (AFDC) database every month. One strength of the MER dataset over the AFDC dataset is that it records 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 simultaneously, one may find many 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 the opening of new stations.

[7] The Port ID does not equate to a single physical port. The EIA assigns a Port ID to every unique combination of access group, network provider, and charging level (e.g., DC fast charger, Level 2). This Port ID subsequently specifies the actual number of ports attached to that specific equipment setup. Therefore, the Port ID count is a count of equipment types, not ports.

Electricity Rate Structures. I compile information on electricity rate schedules from multiple sources. Information about rate schedules dedicated to commercial EV charging is manually collected, while information about the electricity rates in general is downloaded from the US Rate Database (USRDB). So far, rate schedules for 70 investor-owned utility companies are collected, and 20 of them adopt dedicated station rate schedules during the sample period[8]. These utility companies are selected based on the census population they cover. Table 2 lists the treated investor-owned utility companies.

Table 2: List of electricity utilities with dedicated station rate schedules

Utility	Rate Schedule	State	Effective Date	DCFC
Arizona Public Service Co.	DCFC Pilot	AZ	2021-12-01	1
Arizona Public Service Co.	GS-EV Rider	AZ	2022-12-01	
Baltimore Gas & Electric Co.	Demand Charge Credit	MD	2019-07-01	1
Central Maine Power Co.	B-DCFC	ME	2020-07-01	1
Connecticut Light & Power Co.	EV Rate Rider	CT	2019-04-01	
Delmarva Power (Maryland)	Demand Charge Credit	MD	2019-07-01	1
Duquesne Light Co.	EV-TOU Pilot	PA	2021-06-01	
Florida Power & Light Co.	GSD-1EV/GSLD-1EV	FL	2021-01-01	
Gulf Power Co.	GSD-1EV/GSLD-1EV	FL	2022-01-01	
Nevada Power Co.	EVCCR–TOU	NV	2019-04-01	
Northern States Power Co. (Minnesota)	EV Public Charging Pilot	MN	2019-07-17	
Pacific Gas & Electric Co.	BEV-1/BEV-2	CA	2020-05-01	
PECO Energy Co.	EV DCFC Pilot Rider (EV-FC)	PA	2019-07-01	1
Potomac Electric Power Co. (Maryland)	Demand Charge Credit	MD	2019-07-01	1
Public Service Co. of Colorado	S-EV(-CPP)	CO	2021-01-01	
Public Service Co. of New Mexico	Non-Residential Charging Station - Pilot	NM	2022-01-01	
Public Service Co. of Oklahoma	GS-PEV	OK	2022-01-31	
Public Service Elec & Gas Co.	Distribution Demand Charge Rebate	NJ	2021-02-01	1
San Diego Gas & Electric Co.	EV-HP	CA	2022-01-01	
Sierra Pacific Power Co. (Nevada)	EVCCR–TOU	NV	2019-04-01	
Tucson Electric Power Co.	Stand-Alone Electric Vehicle Charging	AZ	2021-07-28	1

Among these twenty investor-owned utility companies who have introduced rate schedules specifically for public EV charging stations, eight companies have rate schedules that apply exclusively to DC fast charging stations, while the other thirteen companies offer rate schedules for general public charging stations. The designs of these rates vary significantly across different utility companies, falling into several distinct categories based on the mechanism used to mitigate demand charges.

The first policy mechanism focuses on demand charge mitigation through load factor limits. This group sets minimum load factor limits to reduce the demand charge burden. Charging stations pay demand charges based on the lower of the actual peak demand me-

[8]Duquesne Light is not included for technical issues in this version of the work.

tered or the limit demand calculated to achieve the minimum load factor. The definition of the load factor is the ratio of the average kWh used over a period of time ($\frac{\text{Total kWh used}}{\text{Number of hours}}$) to the peak kW demand during the same period, or

$$\text{Load Factor} = \frac{\text{Total kWh used}}{\text{Peak kW Demand} * \text{Number of hours}}.$$

As a result, stations with "peaky" load profiles (low load factors) benefit from this mechanism with the minimum load factor limit or the maximum peak kW demand limit. Arizona Public Service Co. directly sets the lower limit for its load factor at 25%. At the same time, Florida Power & Light Co. and Gulf Power Co. compare the peak kW demand with total kWh used divided by 75. The number 75, in turn, implies the load factor of 10.42%. Consequently, Arizona Public Service Co. provides a larger effective discount because its higher load factor limit translates into a lower calculated limit demand compared to the Florida Power & Light Co. or Gulf Power Co.

The second policy group mitigates demand charges through direct discounts and structural rate reductions. This category encompasses utilities that provide a direct financial incentive or implement fundamental structural changes to the rate itself. Direct discounts are offered by utilities such as Baltimore Gas & Electric Co., Delmarva Power (Maryland), Potomac Electric Power Co. (Maryland), and Public Service Elec & Gas Co. offer percentage discounts ranging from 50% to 75% on demand charges. PECO Energy Co. applies a fixed discount based on the total capacity of the charging station, benefiting stations with greater capacity. Other companies modify the rate architecture. Pacific Gas & Electric Co. and San Diego Gas & Electric Co replaced conventional demand rates with significantly lower subscription charges, though slated for an increase in 2025 (?). Utilities like Connecticut Light & Power Co., Nevada Power Co., Sierra Pacific Power Co. (Nevada), and Public Service Co. of New Mexico offer schedules with lower demand rates offset by compensatory higher energy rates. Northern States Power Co. (Minnesota) offers an off-peak discount to encourage load management.

The third group consists of a smaller, distinct set of comprehensive and peak-focused reduction programs. Public Service Co. of Oklahoma and Tucson Electric Power Co.

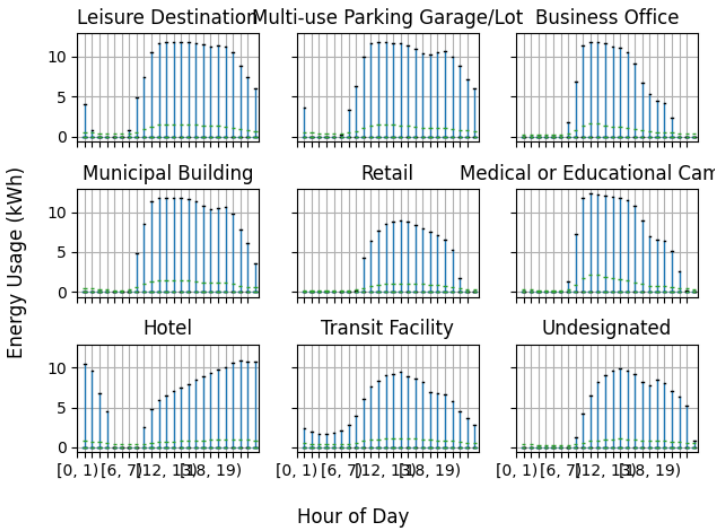
stand out by providing both reduced demand rates and lower energy rates for their EV charging station customers. Similarly, Central Maine Power Co. and Public Service Co. of Colorado use critical peak periods to introduce highly specific rates tied to maximum demand or energy usage during those times.

Finally, a fifth category addresses Time-of-Use Incentives and Pilot Programs designed primarily to shift load consumption. Arizona Public Service Co. offers a rate schedule applicable only to Level 2 charging stations, designed to encourage consumption shifts from on-peak to off-peak periods by offering lower off-peak energy rates. Similarly, Duquesne Light Co. introduced an EV-TOU pilot program that offered TOU supply energy rates for its 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 staff. I download all rate schedule information, including approved and non-approved rate plans, via API provided by the USRDB. The USRDB includes the utility name, the effective period of electricity rates, and detailed rate plans. I merged zip code information using the utility-zip lookup table to generate a utility-zip-quarter panel of electricity rate plans.

Electricity Load Profiles. The EVWATTS database offers observed charging behaviors of individual EV charger from 2019 to 2022. EVWATTS provides various information about charging sessions, for example, when they started, when they ended, and how much electricity was provided. In addition, the data set categorized charging station venues into ten types. Figure 3 illustrates daily distribution of energy usages of level 2 charging stations in each venue. I utilize this data, combined with the comprehensive rate schedules and producer price indix (PPI), to calculate the average monthly electricity bill deflated by the PPI to January 2015 dollars for a Level 2 and a DC fast charging station in each utility area. Specifically, I use the full sample of observed hourly load profiles for charging ports from 2021 and assume this usage pattern is representative for the entire 2015-2022 study period. To translate these profiles into a station-level cost, I address two data limitations. First, since the EVWATTS data does not identify charging port locations and is at the port level, I construct "pseudo-stations" by scaling the port's hourly load profile. Based on the median observed station size in the AFDC dataset, I assume each pseudo-station operates with two identical charging ports (i.e., multiplying the port's hourly load by two). Second, I assume a commercial power rating of 9.6 kW for Level 2 AC chargers (derived from 40A at 240V) (noa, 2024) and 150 kW for DC fast chargers (consistent with the NEVI standard) (Federal Highway Administration (FHWA), 2023). These technical parameters are used to calculate specific rate discounts and demand charge limits applied in some utility rate schedules. For each pseudo-station, I calculate the monthly bill under every utility's rate schedule, which allows us to determine the average bill per utility area. Crucially, by using a single, national sample of observed usage patterns, I avoid the endogeneity concern that would arise if I matched stations to their actual local electricity rates and usage profiles (as both station entry and usage are influenced by those local electricity rates).

Figure 3: Load profile distribution of level 2 charging stations. Blue lines indicate maximum energy usage while green lines indicate mean. Energy usage patterns are different across locations.



Load profile distribution of level 2 charging stations. Blue lines indicate maximum energy usage while green lines indicate mean. Energy usage patterns are different across locations.

Zip Code Business Pattern. The fourth dataset is the Zip Code Business Pattern (ZBP). This dataset provides various information representing zip-code-level business activities, such as the number of establishments, total employment, and annual payroll. I utilize this dataset to control for charging demand using these proxy measures. First, charging demand for public stations is driven by EVs traveling to destinations such as work, shopping centers, or tourist sites, rather than by EVs registered within the zip code. Since the level of business activity is inherently correlated with both the overall vehicle traffic and the number of EVs on the road, I control for zip-code-level business activity to proxy for public charging demand. This approach is particularly effective for modeling Level 2 charging stations, which are predominantly located in urban environments where business activity and traffic volume exhibit a meaningful correlation. Second, I did 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.

State Financial Incentives. Next dataset I use is the Database of State Incentives for Renewables & Efficiency (DSIRE). I filter financial incentive programs related to commercial EV charging stations. Then I construct an indicator variable which is 1 if there is a newly introduced financial incentive program applicable to an electricity utility company territory during the study period. This variable controls for contemporaneous supporting programs, such as installation rebates and grants. Many treated states introduced new incentive programs during the study period. For instance, Tucson Electric Power and Duquesne Light introduced rebate programs in the same quarter as their dedicated station rates. Conversely, PG&E of California and other utilities, including those in Colorado, New Mexico, and Oklahoma, had incentives before their new rates, while another major California utility, SDG&E, and utilities in New Jersey, Connecticut, Maryland, and Minnesota introduced incentives afterward. The potential correlation between these financial incentives and the rate reforms presents a challenge to fully isolating the causal effect of the electricity rate structure change, and a possibility of upward bias in the estimates.

Utility Territories. The last information I utilized 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, utility-zip code pairs are used as unique identifiers.

Table 3: Charging Stations Before Dedicated Station Rates

		Treated	No PG&E	Control
DC Fast	Charging Ports	4.45 (7.56)	3.46 (5.80)	6.10 (6.73)
	Total Charge ($)	2478.69	2641.39	768.16
	Energy Charge ($)	1276.59	1097.32	58.39
	Demand Charge ($)	834.32	1127.28	24.04
	Fixed Charge ($)	367.78	416.80	685.73
Level 2	Charging Ports	18.49 (37.93)	13.89 (25.47)	14.20 (22.78)
	Total Charge ($)	723.39	690.04	698.28
	Energy Charge ($)	390.12	296.66	22.34
	Demand Charge ($)	65.98	101.35	4.49
	Fixed Charge ($)	267.29	292.02	671.45

Notes: This table reports the average number of charging ports in a zipcode area and the average value of electricity charges for a station in a utility territory. Standard errors are in the parentheses.
Data source: EIA, USRDB, Various utility websites, EVWATTS, ZBP, and ACS.

Table 3 reports summary statistics for outcome variables at the zip-code-utility level. The sample is divided into treated territories (data strictly before the intervention period) and control territories (all periods). The statistics reveal notable differences in charging infrastructure levels and electricity cost structures between the groups prior to treatment. For DC fast charging (DCFC) ports, the control territories exhibit a higher average port count (6.10) compared to the treated territories (4.45). This difference is primarily driven by utility territories outside of California; excluding PG&E territory reduces the treated average to 3.46.

The financial metrics highlight a significant divergence in operating environments. DCFC stations in the treated area face substantially higher energy and demand charges compared to those in the control area, though control territories have higher fixed charges. A similar pattern holds for Level 2 charging ports: while port counts are relatively similar between control areas and treated areas (excluding PG&E), stations in the treated group bear significantly higher energy and demand charges while paying lower fixed charges.

This clear divergence in pre-treatment levels and the structure of electricity costs—particularly the high demand charges in future treatment areas—demonstrates that the treated and control groups are not structurally identical. This finding underscores why standard Difference-in-Differences (DID) estimation, which relies on strict level comparisons, would produce biased results. Consequently, advanced methods like Synthetic Difference-in-Differences (SDID) and Local Projection Difference-in-Differences (LPDID) are necessary to construct comparable counterfactual trends by accounting for these observed structural differences.

4 Empirical Methods

This study estimates the effect of dedicated station rates schedules on the deployment of charging ports using two empirical strategies well-suited for staggered treatment adoption: synthetic difference-in-differences and local projection difference-in-differences. To investigate the underlying mechanism, I analyze how the adoption of these rates schedules correlates with electricity charges for station operators.

4.1 Synthetic 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 intervention decision is made 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 difference-in-differences method (SDID) (Arkhangelsky et al., 2021) complements SC by adding features of the difference-in-differences method, adding unit fixed effects and enabling multiple treated units. In addition, SC and SDID could result in unbiased estimates given a good time-consistent fit pre-treatment and works well when only a few utility companies introduced the dedicated rate schedules. In addition, the traditional DID estimator is prone to bias when dedicated station rate schedules are introduced across different utility territories at staggered times, primarily because it relies on "unclean" comparisons between groups that are already treated and those newly entering treatment (Goodman-Bacon, 2021). In contrast, SDID method is explicitly designed to handle staggered intervention by constructing a synthetic counterfactual based on units drawn exclusively from the donor pool of never-treated units, thereby avoiding this comparison bias.

This paper employs SDID to estimate the effect of the dedicated station electricity rate schedules on two sets of outcome variables. The first set is the number of charging ports: DC fast and level 2. The second set of variables is components of the monthly electricity bill faced by charging stations: total charge, energy charge, demand charge, and fixed charge. The analysis for the first set of outcome variables uses a panel data in zip code-year-quarter level. On the other hand, the second set of analysis aggregates data into electric utility-year-quarter level, because all stations in a utility territory will face the same electricity rate schedule. In general, all the analysis uses a balanced panel with N units and T time periods.

In the basic setting with only one treated utility territory, where the first N_{co} units are never-treated group and the last $N_{tr} = N - N_{co}$ units are in the treated group affected by the policy after time T_{pre} at the same time. Therefore, there are $T_{post} = T - T_{pre}$ post exposure time periods. SDID assigns unit weights, $\hat{\omega}_i^{sdid}$, on control groups so that the weighted average of pre-treatment outcomes for control units is parallel to the average outcomes for the treated units prior to the treatment by a constant amount, $\hat{\omega}_0$. This setup resembles how SC methods constructs a synthetic control. The unit weights $\hat{\omega}^{sdid}$ and the intercept $\hat{\omega}_0$ solves a minimization problem with a penalty term so that they 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 $t = 1, \ldots, T_{pre}$. On top of that SDID sets up time weights, $\hat{\lambda}^{sdid}$, so that the weighted average of the pre-treatment outcomes, which are constructed using the time weights for each control units, differs from the average post-treatment outcomes for each of the same control units by a constant, $\hat{\lambda}_0$. The time weights emphasize pre-exposure time periods of the control units that are on average similar to post-exposure time periods of the control units, and satisfies the following relationship: $\hat{\lambda}_0 + \sum_{t=1}^{T_{pre}} \hat{\lambda}_t^{sdid} Y_{it} \approx T_{post}^{-1} \sum_{t=T_{pre}+1}^{T} Y_{it}$ for all $i = 1, \ldots, N_{co}$. This setup insures newly constructed post-treatment part of the synthetic control resembles the post-treatment part of the original control units.

As shown in (1), SDID estimates the average causal effect, $\hat{\tau}^{sdid}$ by regressing the outcome variable on unit dummies, time dummies and the treatment variable D_{it} just like the difference-in-differences method, but using weights on units, $\hat{\omega}_i^{sdid}$, and weights on time periods, $\hat{\lambda}_t^{sdid}$.

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

This equation is like that of difference-in-differences method where $\hat{\omega}_i^{did} = \frac{1}{N_{co}}$ and $\hat{\lambda}_t^{did} = \frac{1}{T_{pre}}$. The resulting estimate, $\hat{\tau}^{sdid}$, also shows the similarity. SDID estimator compares the average change of the outcome variable of treated units and the average change of the outcome variable of control units but in weighted version.

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

Check Arkhangelsky et al. (2021) for more detailed explanation.

In the current dataset, two utility companies, Southern California Edison and Alabama Power Company, are always treated units since its dedicated station rate started prior to the first year in my dataset, and 19 utility companies, including Connecticut Light & Power, Florida Power & Light, and Pacific Gas & Electric, are treated at some point; the other companies are never treated. Zipcode areas in these never-treated utility territories form the donor pool. Then, unit weights for zip codes from the donor pool and time weights for pre-treatment periods are calculated to construct a synthetic control that has parallel trending outcome variables: the number of charging ports or the amount of electricity bills.

4.2 Local Projection Difference-in-Differences (LPDID)

The Local Projection Difference-in-Differences (LPDID) is another way to handle the "unclean" comparisons between already treated groups and newly treated groups. LP-DID further deals with potentially heterogeneous treatment effects, the local projection difference-in-differences estimation is used (Dube et al., 2023). Unlike SDID, LPDID relies on "natural" control units and includes lagged outcome variables as explicit controls. This approach avoids the complexity of synthetic weighting while directly addressing potential violations of the parallel trends assumption through dynamic controls.

$$Y_{i,t+h} - Y_{i,t-1} = \beta_h \Delta D_{i,t} + \Sigma_{k=1}^{p} \gamma_k^h Y_{i,t-k} + X_{it}\Gamma + \delta_t^h + \epsilon_{i,t}^h. \tag{3}$$

As in the SDID analysis, the outcome variable, $Y_{i,t}$ consists of two components: the total number of public EV charging ports (DC fast and Level 2) in zipcode area i at quarter t, and the simulated average monthly bill components (energy, demand, fixed, and total charge) paid by a charging station in that area and quarter. $D_{i,t}$ is an indicator variable which equals 1 if a dedicated station rate schedule is introduced in time t. Different lags of the outcome variables are included to incorporate selection bias, installation bottleneck, and different trends across utility territories. Standard errors are clustered at the 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:

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

5 Results

This section presents the main empirical findings of the paper. I first estimate the causal effect of the new station rate schedules on the deployment of EV charging ports using several econometric models. I then investigate the primary mechanism for this effect by analyzing how the rates changed electricity bills for station operators.

5.1 Charging Ports

The SDID results are displayed in Table 4, which compares the pre-treatment characteristics of the average of actual treated zip code areas with that of the synthetic controls.

Table 4: Effect of Station Rates on EV Charging Port Installation

	(1) SDID	(2) SDID	(3) Linear	(4) Linear
DC Fast				
Post-Station Rate	0.918**	0.920**	3.392***	1.678***
	(0.442)	(0.431)	(0.777)	(0.536)
Obs.	90675	90675	89032	89032
Controls	No	Yes	No	Yes
Level 2				
Post-Station Rate	1.415**	1.453**	10.502***	5.481***
	(0.706)	(0.662)	(2.386)	(1.732)
Obs.	90675	90675	89032	89032
Controls	No	Yes	No	Yes

Notes: This table reports regression estimates from Equation (1), along with corresponding results from linear and Poisson panel fixed-effects models. Standard errors, reported in parentheses, are clustered at utility territory level.
Data source: EIA, USRDB, Various utility websites, EVWATTS, ZBP, and ACS.

Tables 4 presents the main estimates of the effect of new station rates on charging port deployment for DC fast and Level 2 chargers.

My preferred specification, the Synthetic Difference-in-Differences (SDID) model, is shown in columns (1) and (2) of each table. Column (1) is the coefficient from regressing the number of DC fast ports on the indicator variable for the introduction of the dedicated station rate schedule, zip code dummies and year-quarter dummies. In addition, column (2) includes demographic control variables such as the number of establishments, total population, etc. For DC fast chargers, the results indicate that the new rates led to a statistically significant increase of 0.920 additional charging ports per zip code when including demographic controls (column 2). For Level 2 chargers, the effect is slightly larger, with an estimated increase of 1.453 ports (column 2).

For comparison, columns (3) and column (4) present results from standard linear fixed-effects (OLS). While these models also show a positive and significant effect, the estimates are likely biased. The standard fixed-effects estimator is known to produce misleading results with staggered treatment timing, and both models rely on a stricter parallel trends assumption. Therefore, I focus on the SDID results as the most credible estimates of the policy's impact.

Table 5: Effect of Station Rates on EV Charging Port Installation

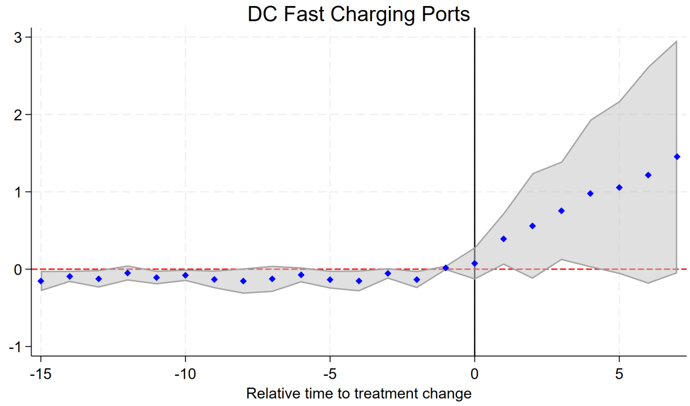
	(1)		(2)	
	Poisson	IRR	Poisson	IRR
DC Fast				
Post-Station Rate	0.811***	2.250***	0.365***	0.365***
	(0.037)	(0.084)	(0.041)	(0.041)
Obs.	72168	72168	72168	72168
Controls	No	No	Yes	Yes
Level 2				
Post-Station Rate	0.599***	1.821***	0.189***	0.189***
	(0.027)	(0.049)	(0.029)	(0.029)
Obs.	85095	85095	85095	85095
Controls	No	No	Yes	Yes

Notes: This table reports regression estimates from Equation (1), along with corresponding results from linear and Poisson panel fixed-effects models. Standard errors, reported in parentheses, are clustered at utility territory level.
Data source: EIA, USRDB, Various utility websites, EVWATTS, ZBP, and ACS.

The charging station entry decision is a dynamic behavior. Figures 4–5 plot the quarterly estimates of the impacts of the introduction of EV charging rate schedules, that is, the quarterly differences in the number of charging ports between real and synthetic zip code areas. Both figures suggest that, on average, the enactment of new rate schedules increased the number of charging ports in a zip code area. The number of DC fast charging ports increased over time to approximately 1.5 ports, passing the average treatment effect of 0.920 ports. The average treatment effect for level 2 ports is about 1.453 port and this effect increases over time to approximately 2 ports.

These changes in the number of charging ports could be due to changes in the electric-

Figure 4: SDID Event Study: Number of DC Fast Charging Ports (All Utility Territories)



Notes: This figure plots the estimated event study coefficients from the SDID analysis for DC fast charging ports. The shaded area is the 95% confidence interval, with standard errors calculated via a placebo method and clustered by zip code. The estimated treatment effect reaches approximately 1.5 additional ports by the seventh quarter post-event and persists thereafter.

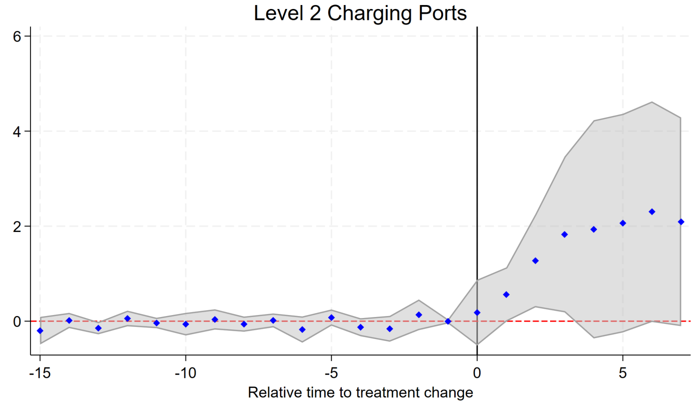
ity rate schedules charging stations face, changes in EV drivers' charging patterns induced by the introduction of new station rates, or just mere coincidence, possibly related to other supporting policies such as installation rebates. Table 6 shows how electricity bills faced by DC fast charging stations and level 2 charging stations changed after the introduction of dedicated station rate schedules.

The LPDID analysis reveals two important dynamics. First, when estimated without controlling for lagged outcome variables, the subfigure (a)'s in Figures 6–7 reveal clear pre-treatment trends. The presence of clear pre-treatment trends indicates that simple Difference-in-Differences (DID) estimates would be biased. This statistical concern, combined with the fact that new rate schedules are often announced before their effective date, strongly underscores the necessity of controlling for pre-treatment outcome dynamics in the full model specification.

After controlling for these dynamics, the results for DC fast chargers confirm our main SDID findings. As shown in Figure 6, the number of charging ports grows steadily following the rate adoption, with the effect reaching approximately two additional ports per zip code after 10 quarters.

In contrast, the results for Level 2 chargers suggest a potential violation of the parallel trends assumption, even after controlling for pre-treatment outcomes (Figure 7). The

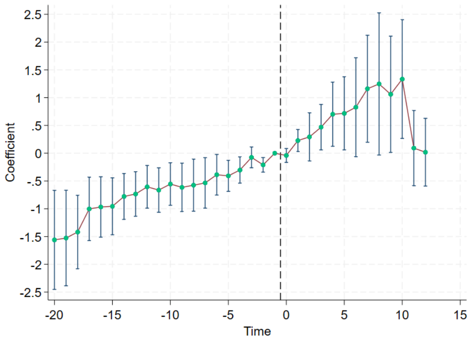
Figure 5: SDID Event Study: Number of Level 2 Charging Ports (All Utility Territories)



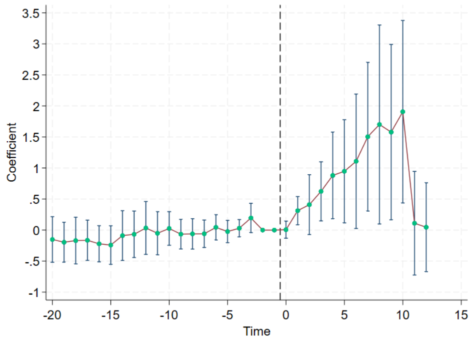
Notes: This figure plots the estimated event study coefficients from the SDID analysis for Level 2 charging ports. The shaded area is the 95% confidence interval, with standard errors calculated via a placebo method and clustered by zip code. The estimated treatment effect reaches approximately two additional ports by the sixth quarter post-event.

Figure 6: LPDID: Number of DC Fast Charging Ports (All Utility Territories)

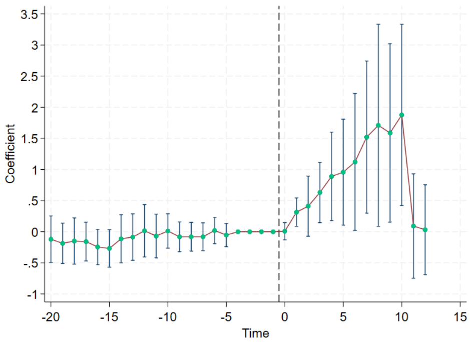
(a) DC Fast: Lag 0



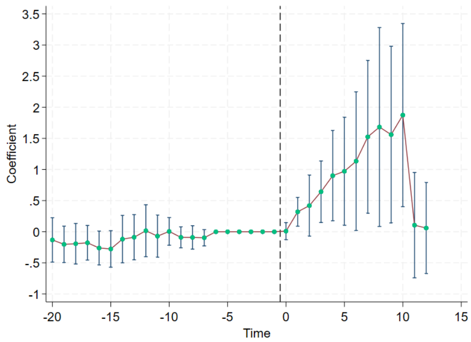
(b) DC Fast: Lag 2



(c) DC Fast: Lag 4

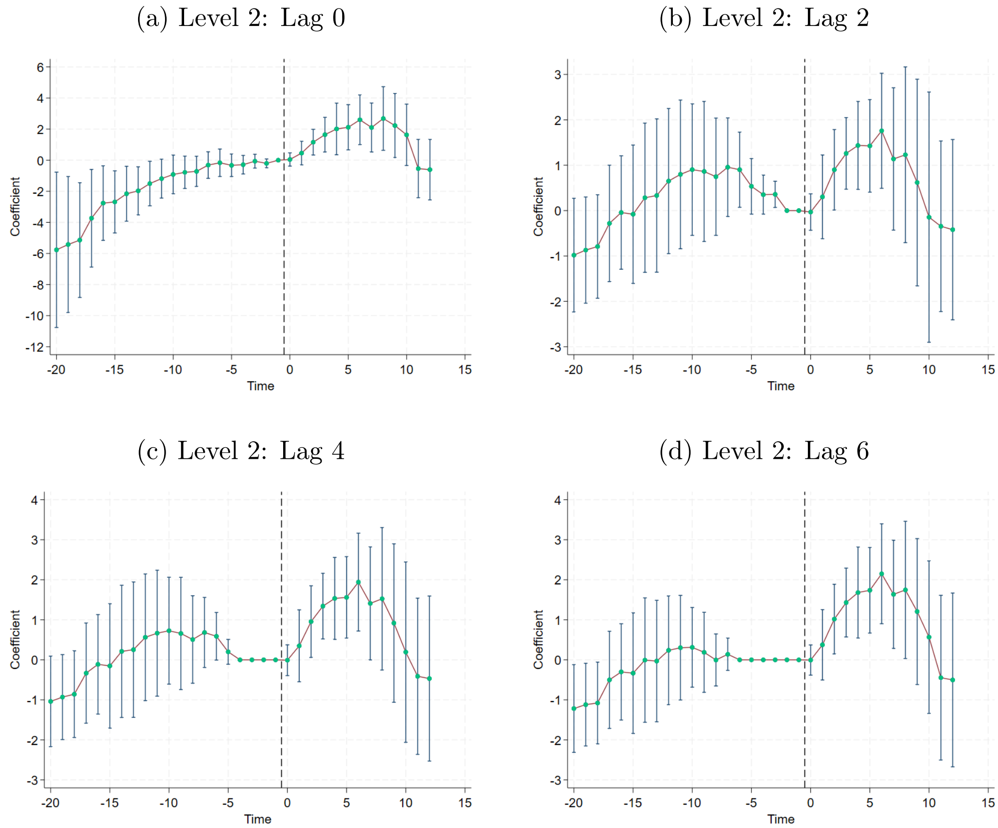


(d) DC Fast: Lag 6



Note: This figure plots estimated LPDID coefficients for the number of DC fast charging ports in a zip code area by quarter. All standard errors are clustered at the utility level.

Figure 7: LPDID: Number of Level 2 Charging Ports (All Utility Territories)



(a) Level 2: Lag 0

(b) Level 2: Lag 2

(c) Level 2: Lag 4

(d) Level 2: Lag 6

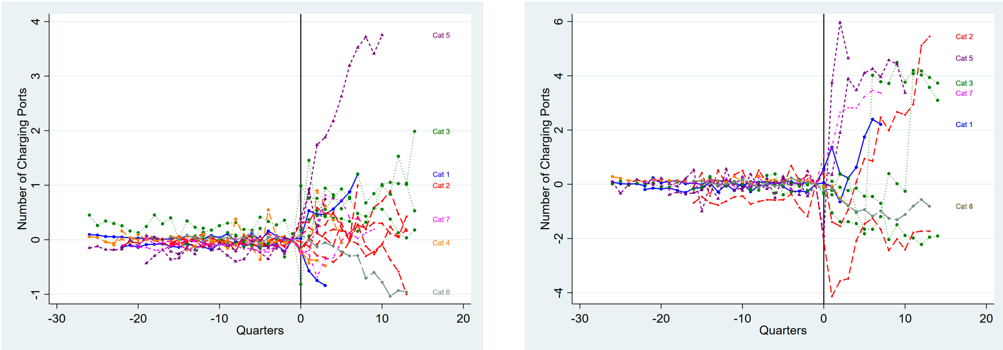
Note: This figure plots estimated LPDID coefficients for the number of level 2 charging ports in a zip code area by quarter. All standard errors are clustered at the utility level.

number of ports appears to increase leading up to the rate change before reverting to the baseline level. This pattern could stem from several sources: first, station owners may be postponing installations in anticipation of the new, more favorable rate schedules; second, the treatment and control zip codes may differ in unobserved ways that are not captured by the model; thrid, the pre-treatment trend for Level 2 chargers is estimated using a smaller subset of utilities, potentially reflecting greater heterogeneity in installation patterns across service territories compared to DC fast chargers.

Figure 8 reports SDID event study results for regressing the number of charging ports on the introduction of dedicated station rates with other control variables by each individual utility companies. There are seven categories of dedicated station rate designs. Category 1 includes Florida Power & Light and Gulf Power. Category 1 utility companies introduced load factor limits to their new station rates. Category 2 includes Baltimore

Figure 8: SDID Event Study: Number of EV Charging Ports (by Utility Categories)

(a) DC Fast (b) Level 2



Note: This figure plots estimated SDID event study coefficients for the number of charging ports. Each line represents a utility company that introduced dedicated station rates. Lines with the same color and the same marker represent utility companies in the same category, or with a similar rate design. Category 1 includes Florida Power & Light and Gulf Power. Category 1 utility companies introduced load factor limits to their new station rates. Category 2 includes Baltimore Gas & Electric, Delmarva Power , PECO Energy, Potomac Electric Power, and Public Service Elec & Gas. Category 2 utility companies offered instant discount for demand charges. Category 3 includes Connecticut Light & Power, Nevada Power, Public Service Co of NM, Sierra Pacific Power. Category 3 companies lowered demand rates but increased energy rates. Category 4 includes Public Service Co of Oklahoma and Tucson Electric Power. Category 4 utility companies introduced station rates with lower demand rates and lower energy rates relative to their similar general service rates. Category 5 includes Pacific Gas & Electric and San Diego Gas & Electric. Category 5 utility companies introduced dedicated station rates with subscription charges, which substitutes demand charges but set at lower level. Category 6 includes Northern States Power. This company introduced a dedicated station rate with discounted off-peak demand rate. Category 7 includes Central Maine Power and Public Service Co of Colorado. Category 7 utility companies introduced station rate schedules with critical peak rates.

Gas & Electric, Delmarva Power , PECO Energy, Potomac Electric Power, and Public Service Elec & Gas. Category 2 utility companies offered instant discount for demand charges. Category 3 includes Connecticut Light & Power, Nevada Power, Public Service Co of NM, Sierra Pacific Power. Category 3 companies lowered demand rates but increased energy rates. Category 4 includes Public Service Co of Oklahoma and Tucson Electric Power. Category 4 utility companies introduced station rates with lower demand rates and lower energy rates relative to their similar general service rates. Category 5 includes Pacific Gas & Electric and San Diego Gas & Electric. Category 5 utility companies introduced dedicated station rates with subscription charges, which substitutes demand charges but set at lower level. Category 6 includes Northern States Power. This company introduced a dedicated station rate with discounted off-peak demand rate. Category 7 includes Central Maine Power and Public Service Co of Colorado. Category 7 utility companies introduced station rate schedules with critical peak rates. The results shown highlight the heterogeneous impacts of the dedicated station rates on both DC fast charging ports and level 2 charging ports across different utilities. Even utility territories within the same category faced different effects, for example DC fast charging stations for Florida Power & Light and Gulf Power in Category 1. Therefore, this heterogeneous effects cannot be solely explained by different rate designs. This phenomenon is especially visible for level 2 charging ports. One reason could be other factors affecting the installation decisions. These charging stations tend to be located near retail businesses and intended to attract customers Arlt and Astier (2023). Changes in the local retail environment may happened at the same time.

5.2 Electricity Bills

This subsection examines whether the new station rate schedules achieved their primary objective of reducing electricity costs, with a particular focus on demand charges.

The first panel of Table 6 shows the estimated impact of the new station rates on various components of the electricity bill for DC fast charging stations. The monthly energy charge and demand charge decreased after the introduction of dedicated station rates by $686 and $421, respectively. These estimates are statistically significant. While the point estimates suggest a $318 increase in fixed charges, this change is not statistically significant. The resulting estimated net decrease of $995 in the total monthly bill is statistically insignificant.

The second panel of 6 show the estimated impact of the new station rates on various components of the electricity bill for level 2 charging stations. For Level 2 charging stations, the new rates had statistically significant but opposing effects on different components of the electricity bill. Specifically, average monthly energy charges significantly decreased by $99, while demand charges significantly increased by $85. These two effects

Table 6: Effect of Station Rates on Electricity Charges

	(1) Total	(2) Total	(3) Energy	(4) Energy	(5) demand	(6) demand	(7) fixed	(8) fixed
DC Fast								
Post-Station Rate	-1017**	-995	-683***	-686***	-417***	-421***	280	318
	(416)	(607)	(26)	(26)	(29)	(28)	(438)	(906)
Obs.	2294	2294	2294	2294	2294	2294	2294	2294
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Level 2								
Post-Station Rate	458	492	-97***	-99***	85***	85***	454	493
	(754)	(906)	(11)	(12)	(11)	(7)	(758)	(1644)
Obs.	2077	2077	2077	2077	2077	2077	2077	2077
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Note: This table shows regression results from equation (1). Standard errors in parentheses are robust to serial correlation within utility territories. Data source: EIA, USRDB, Various utility websites, EVWATTS, ZBP, and ACS.

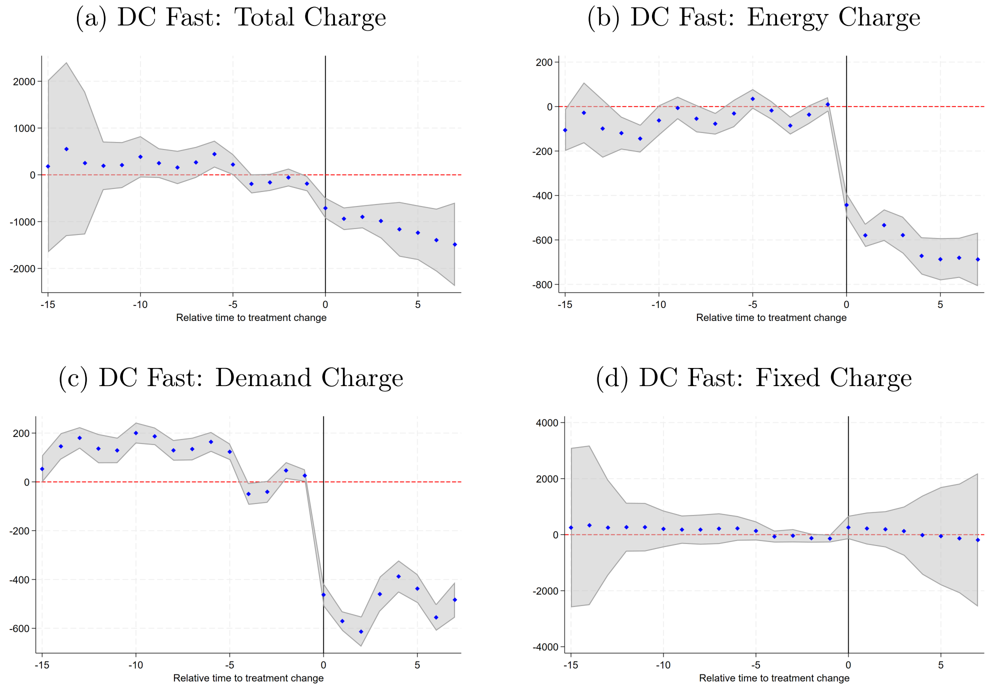
largely offset each other. Furthermore, while the point estimate for fixed charges shows a substantial increase of \$493, this change is not statistically significant. As a result of these counteracting and insignificant effects, the net increase of \$492 in the total monthly bill is not statistically significant.

The finding that demand charges increased for Level 2 stations is seemingly paradoxical, as many utilities advertised the new rates as offering discounted demand charges. However, this result is driven by the fact that the pre-treatment rate schedules applicable to many charging stations, particularly for Level 2, often had no demand charges at all.

For instance, Florida Power & Light previously offered a "General Service Non-Demand" rate. Their new, specialized station rate introduced demand charges reinforced with load factor limits. Similarly, Pacific Gas & Electric's common "A-1" rate lacked a demand charge, whereas their new station rates include a subscription fee that functions as one. Thus, for a significant number of stations, the "discounted" new rate represented the introduction, not the reduction, of demand-based fees.

Figures 9–10 illustrate the dynamic effects of the new rates on electricity bills for both DC fast and Level 2 charging stations.

Figure 9: SDID Event Study: Average Monthly Bill for DC Fast Charging (All Utility Territories)



Note: This figure plots estimated SDID event study coefficients for the average electricity charges a simulated DC fast charging stations would face in each utility territories. Shaded area is the 95% confidence interval based on standard errors that are calculated using placebo method, clustered at utility level.

For DC fast chargers, the results shown in Figure 9 are consistent with our main findings. I observe a statistically significant decrease in demand charges over time. In contrast, the concurrent decrease in energy charges and increase in fixed charges are not statistically significant.

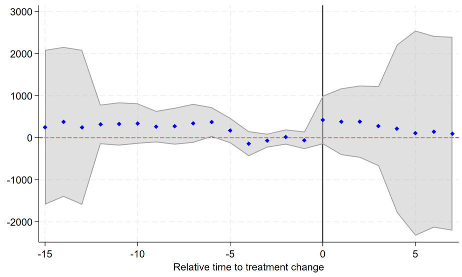
For Level 2 chargers, the dynamics shown in Figure 10 also align with the main results. The new rates led to a significant decrease in energy charges, which was offset by a significant increase in demand charges. The increase in fixed charges was not statistically significant, and consequently, the net effect on the total bill was also insignificant.

As a robustness check on the dynamic bill impacts, Figures 11–12 present the results from the LPDID models, including controls for pre-treatment lags. These findings confirm the dynamic patterns observed in the SDID event studies.

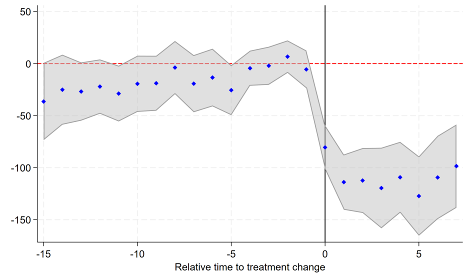
For DC fast chargers (Figure 11), the LPDID plots reinforce a key finding: a persistent and statistically significant decline in demand charges following the introduction of the

Figure 10: SDID Event Study: Average Monthly Bill for Level 2 Charging (All Utility Territories)

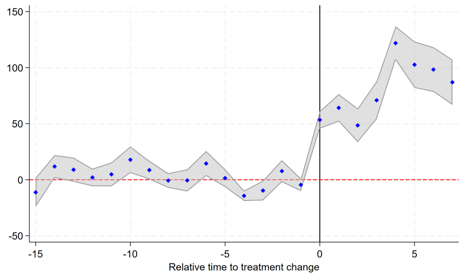
(a) Level 2: Total Charge



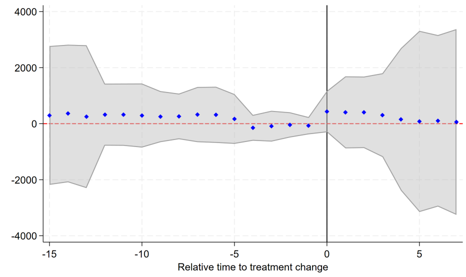
(b) Level 2: Energy Charge



(c) Level 2: Demand Charge



(d) Level 2: Fixed Charge



Note: This figure plots estimated SDID event study coefficients for the average electricity charges a simulated level 2 charging stations would face in each utility territories. Shaded area is the 95% confidence interval based on standard errors that are calculated using placebo method, clustered by utility. Energy Charge decreased by $150 canceling out the increase of demand charge. As a result, changes in the total charge follows that of fixed charge.

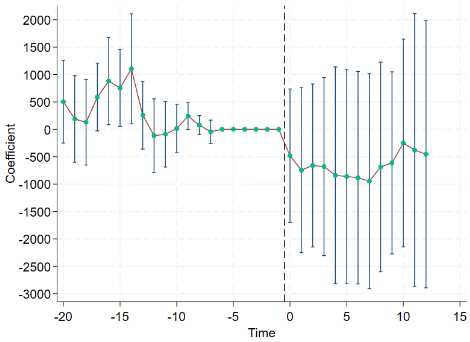
new rates.

For Level 2 chargers (Figure 12), the plots again highlight the counteracting effects. They show a clear and significant drop in energy charges that occurs simultaneously with a significant rise in demand charges post-treatment, confirming that the dynamics observed in the SDID model are not an artifact of that specific estimation strategy.

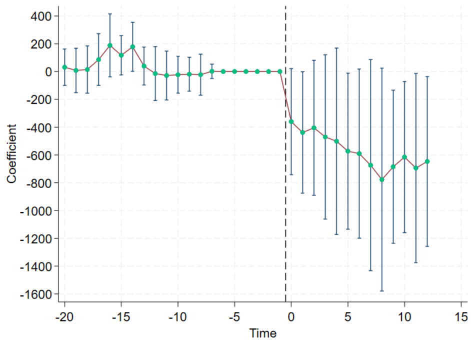
The aggregate results mask two important sources of heterogeneity. First, the large confidence intervals in our main estimates are driven by significant variation in effects across different types of rate structures. As shown in Figures 13–14, which disaggregate the results by rate category, the impact on electricity bills is far from uniform. For DC fast chargers (Figure 13), while most rate types led to a decrease in total charges, some resulted in an increase. These increases were driven by different factors, such as

Figure 11: LPDID: Average Monthly Bill for DC Fast Charging (All Utility Territories)

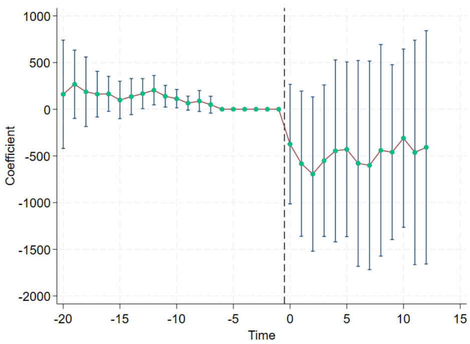
(a) Total Charge



(b) Energy Charge



(c) Demand Charge



(d) Fixed Charge

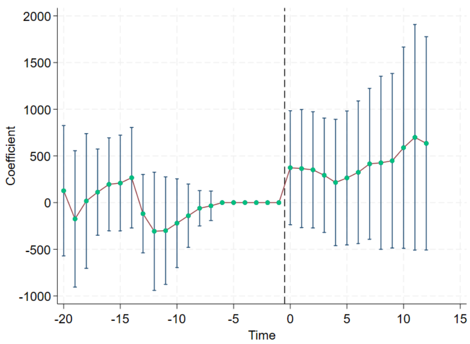
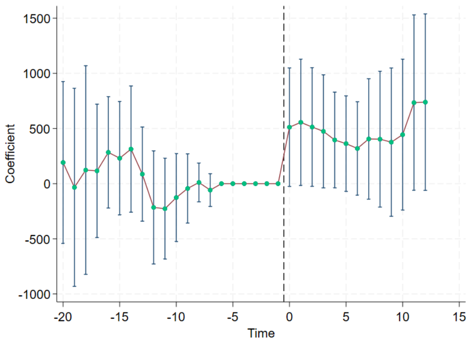
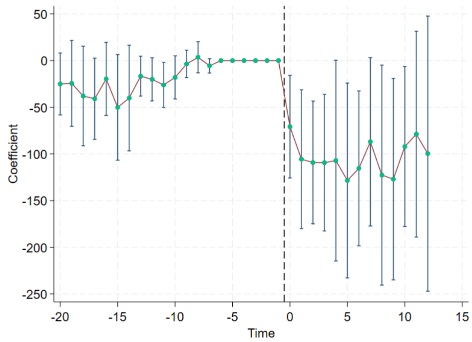


Figure 12: LPDID: Average Monthly Bill for Level 2 Charging (All Utility Territories)

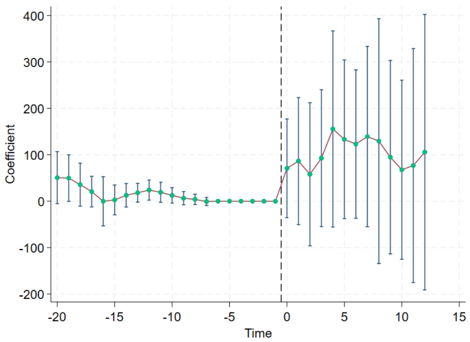
(a) Total Charge



(b) Energy Charge



(c) Demand Charge



(d) Fixed Charge

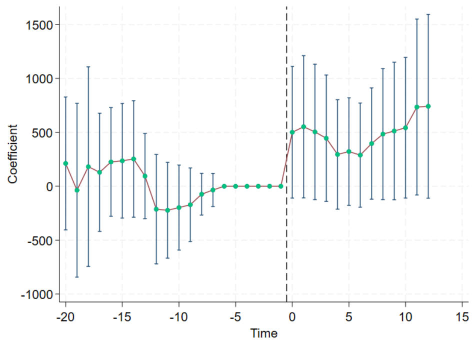
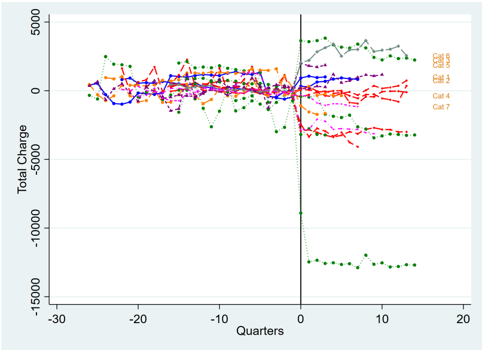
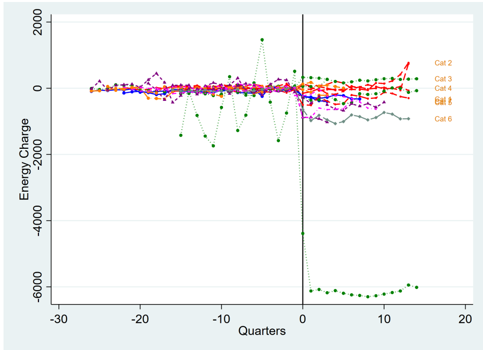


Figure 13: SDID Event: Average Monthly Bill for DC Fast Charging (by Utility Categories)

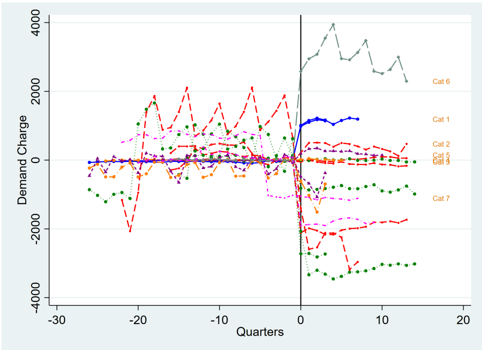
(a) DC Fast: Total Charge



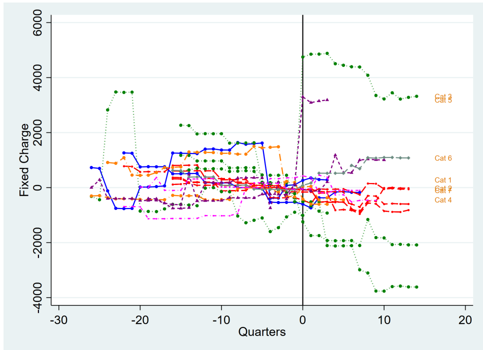
(b) DC Fast: Energy Charge



(c) DC Fast: Demand Charge



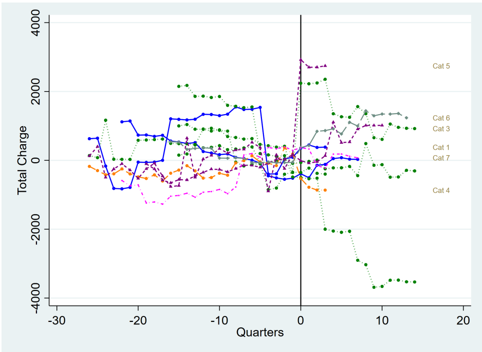
(d) DC Fast: Fixed Charge



Note: This figure plots estimated SDID event study coefficients for the average electricity charges a simulated DC fast charging stations would face in each utility territories. Each line represents a group of utility companies that introduced dedicated station rates in the same quarter. Lines with the same color and the same marker represent utility companies with similar rate categories. Category 1 includes Florida Power & Light and Gulf Power. Category 1 utility companies introduced load factor limits to their new station rates. Category 2 includes Baltimore Gas & Electric, Delmarva Power , PECO Energy, Potomac Electric Power, and Public Service Elec & Gas. Category 2 utility companies offered instant discount for demand charges. Category 3 includes Connecticut Light & Power, Nevada Power, Public Service Co of NM, Sierra Pacific Power. Category 3 companies lowered demand rates but increased energy rates. Category 4 includes Public Service Co of Oklahoma and Tucson Electric Power. Category 4 utility companies introduced station rates with lower demand rates and lower energy rates relative to their similar general service rates. Category 5 includes Pacific Gas & Electric and San Diego Gas & Electric. Category 5 utility companies introduced dedicated station rates with subscription charges, which substitutes demand charges but set at lower level. Category 6 includes Northern States Power. This company introduced a dedicated station rate with discounted off-peak demand rate. Category 7 includes Central Maine Power and Public Service Co of Colorado. Category 7 utility companies introduced station rate schedules with critical peak rates.

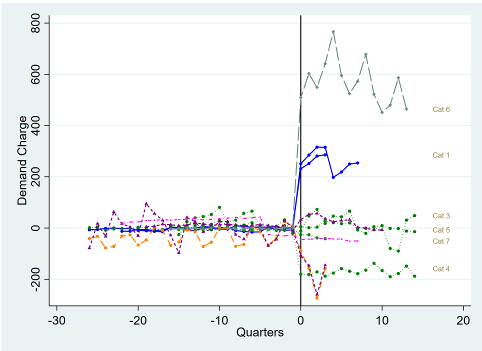
Figure 14: SDID Event: Average Monthly Bill for Level 2 Charging (by Utility Categories)

(a) Level 2: Total Charge

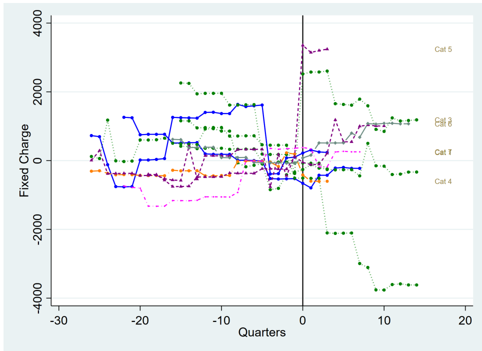


(b) Level 2: Energy Charge

(c) Level 2: Demand Charge



(d) Level 2: Fixed Charge



Note: This figure plots estimated SDID event study coefficients for the average electricity charges a simulated DC fast charging stations would face in each utility territories. Each line represents a group of utility companies that introduced dedicated station rates in the same quarter. Lines with the same color and the same marker represent utility companies with similar rate categories. Category 1 includes Florida Power & Light and Gulf Power. Category 1 utility companies introduced load factor limits to their new station rates. Category 2 includes Baltimore Gas & Electric, Delmarva Power , PECO Energy, Potomac Electric Power, and Public Service Elec & Gas. Category 2 utility companies offered instant discount for demand charges. Category 3 includes Connecticut Light & Power, Nevada Power, Public Service Co of NM, Sierra Pacific Power. Category 3 companies lowered demand rates but increased energy rates. Category 4 includes Public Service Co of Oklahoma and Tucson Electric Power. Category 4 utility companies introduced station rates with lower demand rates and lower energy rates relative to their similar general service rates. Category 5 includes Pacific Gas & Electric and San Diego Gas & Electric. Category 5 utility companies introduced dedicated station rates with subscription charges, which substitutes demand charges but set at lower level. Category 6 includes Northern States Power. This company introduced a dedicated station rate with discounted off-peak demand rate. Category 7 includes Central Maine Power and Public Service Co of Colorado. Category 7 utility companies introduced station rate schedules with critical peak rates.

higher energy charges in Category 1 versus higher demand charges in Category 7. This heterogeneity also reveals that not all utilities succeeded in their stated goal of lowering demand charges.

Second, the new rates had systematically different effects on DC fast chargers compared to Level 2 stations, particularly regarding demand charges . While both station types often saw decreases in energy charges, the impact on demand charges diverged. For Level 2 stations, demand charges increased in most utility territories. In contrast, the effect on demand charges for DC fast chargers was mixed, varying across different rate designs. This increase in demand charges for Level 2 stations, in particular, is due to a paradoxical consequence of the rate shift: many charging stations were previously not subject to any demand rates due to low usage under former commercial rate schedules. Therefore, shifting to a new dedicated station rate—even one advertised as having a "low" or "discounted" demand rate—resulted in the introduction, rather than the reduction, of demand charges for these stations. For instance, while Category 1 utilities introduced load factor limits intended to cap demand charges, stations in these territories were previously often applicable to use non-demand commercial rates. Consequently, upon moving to the new dedicated rates, their demand charges increased. The same happened to Category 5 utility companies.

6 Conclusion and Limitations

This paper investigates the impact of specialized electricity rates on the deployment of public EV charging infrastructure. Using a synthetic difference-in-differences (SDID) approach, I find that the introduction of these rates led to a significant increase in charging infrastructure, adding approximately 0.920 DC fast charging (DCFC) ports and 1.453 Level 2 ports per zip code on average. The primary mechanism for this effect, particularly for DCFC stations, was the reduction of burdensome demand charges, which my analysis shows decreased by a statistically significant $568 per month in treated areas. These results are robust to alternative specifications, and dynamic analysis from event studies and local projection models confirms that these effects emerge and grow in the years following the policy change.

These findings provide strong evidence that electricity rate design can offer a complementary tool to traditional installation subsidies. By constructing an enriched policy portfolio, introducing the new dedicated station rate schedules can accelerate EV infrastructure growth, The results suggest that by alleviating a key component of operating costs—high demand charges—state governments can effectively stimulate private investment in charging infrastructure, particularly for the fast chargers crucial for long-distance travel and driver confidence. Kavianipour et al. (2022) indicates that faster or more powerful chargers could dramatically reduce average waiting time, this result indicates that dedicated station rates could enhance social welfare.

However, the analysis also reveals that the design of the electricity rates is critical. The effects are highly heterogeneous and depend on both the type of charger and the pre-existing rate landscape. For Level 2 chargers, which often were subject to non-demand rates, the shift to new dedicated station rate schedules sometimes paradoxically introduced demand charges, creating a barrier to entry instead of removing it. This highlights potential equity and efficiency trade-offs. Policies that disproportionately favor DC fast charging may neglect the needs of drivers who rely on slower, more affordable Level 2 charging, or who lack access to home charging. A "one-size-fits-all" approach to rate reform is unlikely to be optimal; achieving broad and equitable infrastructure growth may require separate, carefully designed rate structures for different charging technologies.

This study has several limitations that open avenues for future work. First, the analysis relies on simulated electricity bills derived from national load profiles. This simulation approach may not fully capture the complex, real-world diversity of station utilization patterns, which could influence cost estimations. Second, the results represent the average effect across a specific set of early-adopting utilities. The calculated impacts may thus differ as a broader and more diverse group of utilities implement similar programs in the future.

Future research could build on these findings in several ways. First, incorporating granular, real-world electricity consumption data from charging stations would allow for a more precise estimation of the financial impacts of different rate structures. Second, as more utilities adopt these dedicated rate schedules, examining the long-term effects on market structure, station profitability, and consumer charging behavior will be crucial. Finally, exploring the general equilibrium effects, such as the impact of increased charging on local distribution grids and overall electricity prices, remains an important and unanswered question.

Figures

Figure 15: The number of Level 2 and DC Fast charging ports

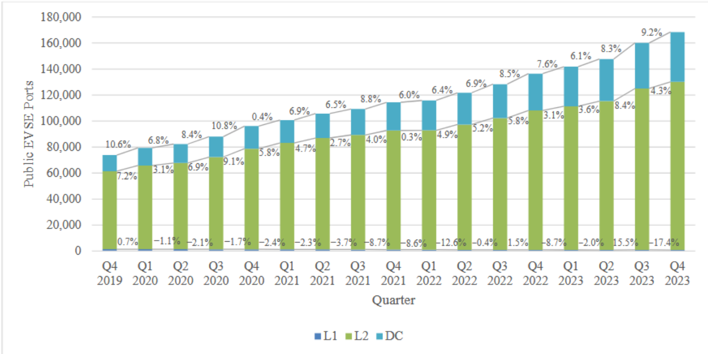


Figure 4. Quarterly growth of public EV charging ports by charging level.

Note: Figure excludes legacy EV charging ports that are not classified by charging level and are no longer manufactured. As of Q4, there were 26 public legacy EV charging ports in the Station Locator. Additionally, the percentages in this figure indicate the percent growth between each quarter.

Note: The number of level 2 and DC fast charging ports has increased from 2019Q4 to 2023Q4. Level 2 chargers are the most prevalent, but the number of DC fast charging ports experienced faster growth.

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Appendix

.1 Ports vs. Bills

In this section, I estimate the correlation between the electricity bill and the number of charging ports across all utility companies. This analysis relies on the general, cross-sectional and temporal variation in electricity rate schedules observed throughout the sample, rather than isolating the causal variation stemming solely from the introduction of dedicated station rate schedules.

Table 7: Electricity Charges vs. EV Charging Port Installation

	(1) Linear	(2) Linear	(3) Poisson	(4) IRR	(5) Poisson	(6) IRR
DC Fast						
Total Charge	0.504		-0.006	0.994		
	(0.646)		(0.009)	(0.009)		
Energy Charge		-17.179*			-0.037	0.963
		(9.282)			(0.025)	(0.024)
Demand Charge		19.909			0.015	1.015
		(18.983)			(0.026)	(0.027)
Fixed Charge		0.593			-0.003	0.997
		(0.568)			(0.006)	(0.006)
Obs.	2294	2294	2294	2294	2294	2294
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Level 2						
Total Charge	0.780		0.007	1.007		
	(1.235)		(0.005)	(0.005)		
Energy Charge		-76.528			0.185**	1.203**
		(157.631)			(0.094)	(0.113)
Demand Charge		410.797			0.232	1.261
		(315.688)			(0.205)	(0.259)
Fixed Charge		1.090			0.006*	1.006*
		(1.470)			(0.004)	(0.004)
Obs.	2077	2077	2077	2077	2077	2077
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows results of regressing total number of charging ports on electricity charges using linear panel fixed effects model and Poisson fixed effects model. Standard errors in parentheses are robust to serial correlation within utility territories. The electricity charges are in $1,000.
Data source: EIA, USRDB, Various utility websites, EVWATTS, ZBP, and ACS.

Table 7 presents results from the panel fixed effects model and th Poisson fixed effects model regressing the number of ports on electricity charges. It is important to note that this specification does not identify a causal relationship and is likely biased by omitted variables (e.g., local demand). The results show some statistically significant correlations, but it is necessary to run a quasi-experimental research design to isolate the causal effect of rate changes from other confounding factors.

.2 Tables

Table 8: Charging Stations Before Dedicated Station Rates: By Category

		Cat1	Cat2	Cat3	Cat4	Cat5	Cat6	Cat7	Cat8	Control
	Charging Ports	3.73	2.72	2.81	6.47	7.35	0.87	3.14	3.44	6.10
DC Fast		(6.30)	(5.00)	(4.88)	(7.24)	(10.39)	(1.57)	(4.72)	(4.88)	(6.73)
	Total Charge ($)	755.01	2974.80	6958.22	1759.44	2136.26	1186.76	1598.91	1891.59	768.16
	Energy Charge ($)	709.66	677.70	3712.56	668.91	1686.96	1096.19	376.60	170.79	58.39
	Demand Charge ($)	2.15	1981.05	2361.08	592.60	106.45	0.00	608.03	1549.65	24.04
	Fixed Charge ($)	43.19	316.04	884.58	497.93	342.85	90.57	614.28	171.15	685.73
	Charging Ports	12.10	.	8.06	3.29	28.47	4.13	17.72	15.05	14.20
Level 2		(19.65)		(12.43)	(3.58)	(52.44)	(5.96)	(28.50)	(19.89)	(22.78)
	Total Charge ($)	306.32	.	713.13	919.79	908.99	442.80	619.54	1043.74	698.28
	Energy Charge ($)	263.41	.	229.60	168.83	566.11	342.60	195.11	381.28	22.34
	Demand Charge ($)	0.70	.	334.20	176.69	20.66	0.00	0.00	133.05	4.49
	Fixed Charge ($)	42.21	.	149.33	574.27	322.22	100.20	424.43	529.41	671.45

Table 9: Charging Stations Before Dedicated Station Rates: All Treated

		APS	BGE	CLP	CME	DLC	DPL	FPL	Control
	Charging Ports	4.09 (5.41)	2.48 (3.98)	2.09 (4.12)	3.58 (5.51)	2.00 (3.09)	3.18 (4.35)	3.84 (6.44)	6.10 (6.73)
DC Fast	Total Charge ($)	2213.68	2396.45	13740.48	3930.26	1180.30	789.58	732.47	768.16
	Energy Charge ($)	-213.44	673.01	8036.23	861.32	1019.27	789.58	690.75	58.39
	Demand Charge ($)	2225.73	682.24	3994.69	2863.64	56.65	0.00	0.00	24.04
	Fixed Charge ($)	201.39	1041.20	1709.56	205.29	104.37	0.00	41.72	685.73
	Charging Ports	18.89 (21.72)	.	6.78 (8.77)	.	6.58 (11.52)	.	12.65 (20.18)	14.20 (22.78)
Level 2	Total Charge ($)	1043.74	.	1060.10	.	nan	.	296.85	698.28
	Energy Charge ($)	381.28	.	278.57	.	nan	.	256.21	22.34
	Demand Charge ($)	133.05	.	631.31	.	nan	.	0.00	4.49
	Fixed Charge ($)	529.41	.	150.22	.	nan	.	40.63	671.45

Table 10: Charging Stations Before Dedicated Station Rates: All Treated

		GPC	NPC	NSP	PECO	PEPCO	PG&E	PNM	Control
	Charging Ports	2.20 (3.55)	1.97 (3.35)	0.87 (1.57)	1.00 (2.07)	2.91 (5.73)	7.19 (10.62)	3.57 (4.96)	6.10 (6.73)
DC Fast	Total Charge ($)	1079.60	657.33	1186.76	2645.40	1114.10	2025.74	3736.67	768.16
	Energy Charge ($)	982.08	579.98	1096.19	414.37	1002.74	1775.65	292.32	58.39
	Demand Charge ($)	33.18	0.10	0.00	2190.49	28.46	18.79	2842.36	24.04
	Fixed Charge ($)	64.34	77.25	90.57	40.54	82.90	231.30	601.99	685.73
	Charging Ports	4.20 (4.49)	10.17 (18.08)	4.13 (5.96)	.	.	27.41 (53.42)	8.64 (10.95)	14.20 (22.78)
Level 2	Total Charge ($)	442.68	249.57	442.80	.	.	785.59	445.96	698.28
	Energy Charge ($)	367.03	172.21	342.60	.	.	564.42	326.66	22.34
	Demand Charge ($)	10.70	0.14	0.00	.	.	0.00	0.37	4.49
	Fixed Charge ($)	64.94	77.22	100.20	.	.	221.17	118.93	671.45

Table 11: Charging Stations Before Dedicated Station Rates: All Treated

		PSC	PSE&G	PSO	SDG&E	SPPC	TEP	Control
	Charging Ports	3.03 (4.50)	3.83 (6.48)	8.12 (7.84)	8.05 (9.33)	5.25 (7.25)	3.17 (4.49)	6.10 (6.73)
DC Fast	Total Charge ($)	970.47	4970.93	1921.19	2626.95	2746.14	1435.94	768.16
	Energy Charge ($)	245.94	685.27	458.02	1293.18	498.17	1090.69	58.39
	Demand Charge ($)	0.00	4230.72	888.90	495.63	1878.15	0.00	24.04
	Fixed Charge ($)	724.53	54.94	574.27	838.13	369.83	345.24	685.73
	Charging Ports	17.72 (28.50)	.	3.29 (3.58)	33.16 (47.86)	7.50 (10.16)	.	14.20 (22.78)
Level 2	Total Charge ($)	619.54	.	919.79	1456.89	769.20	.	698.28
	Energy Charge ($)	195.11	.	168.83	573.59	146.85	.	22.34
	Demand Charge ($)	0.00	.	176.69	112.41	349.15	.	4.49
	Fixed Charge ($)	424.43	.	574.27	770.89	273.20	.	671.45