Can Expanding Charging Infrastructure Boost Plug-in Electric Vehicle Adoption? Evidence from Charging on Higher Education Institutions Campuses

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Honors Seminar: Special Problems in Economics
Spring 2024

Abstract
I compile a unique dataset on plug-in electric vehicle charging at 13 HEIs in New York and Massachusetts. Using a staggered differences-in-differences design, I estimate the impact of adding charging stations on PEV adoption and station utilization. I find that adding the first station attracts 1-2 unique users each week, who together drain 24.2 kWh from stations each day. Each subsequent charging station increases PEV adoption by less than one unique user each week, and meaningfully increases station utilization about five kWh daily. These results indicate that drivers are likely supplementing charging at home with charging on-campus, rather than relying on charging on-campus as their main source of re-fueling. I also find diminishing marginal returns to both PEV adoption and station utilization, which suggests there is a limit to the extent to which HEIs can encourage charging on-campus.

Keywords: plug-in electric vehicle adoption, electric vehicle charging infrastructure, congestion, charge anxiety, HEI sustainable development

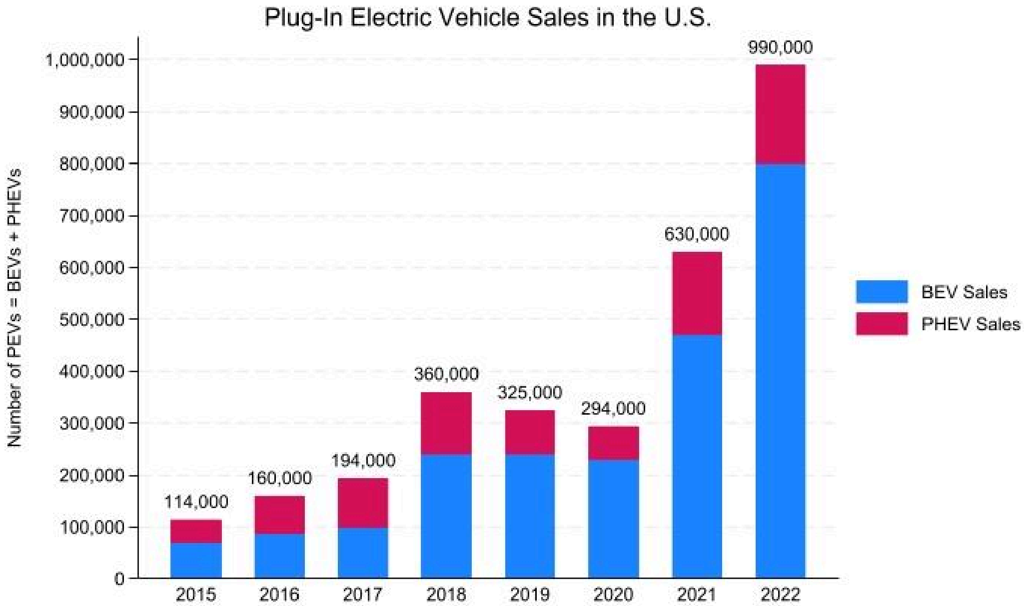
JEL Codes: L62:Automobiles; Other Transportation Equipment; Related Parts and Equipment
L94: Electric Utilities
R42: Government and Private Investment Analysis; Road Maintenance; Transportation Planning
Q56: Environment and Development; Environment and Trade; Sustainability; Environmental Accounts and Accounting; Environmental Equity; Population Growth

Acknowledgements
I'd like to thank Professor Isla Globus-Harris and Professor Benjamin Anderson for their insight and support throughout the research process.

I. Introduction

Most automobiles on the road are powered by either gas or diesel (these are known as conventional vehicles, or CVs); however, sales of plug-in electric vehicles (PEVs), which are a subset of electric vehicles that run by drawing electricity from an external power source, are on the rise (Soltani-Sobh 2017). PEVs can be either battery electric vehicles (BEVs), which must be charged to run, or plug-in hybrid electric vehicles (PHEVs), which can run on either gas or electricity. Figure 1 illustrates the growing popularity of PEVs among U.S. consumers broken down by BEVs and PHEVs. While many more BEVs than PHEVs have been sold every year, total sales of PEVs grew steadily from 2015 to 2018, and has more than doubled since then to just under 1,000,000 vehicles in 2022 (IEA 2023). Monthly sales data from WardAuto finds that over 1,400,000 plug-in electric vehicles were sold last year, more than any previous year's total (Argonne National Laboratory, 2023). The ongoing upward trend in PEV sales indicates that consumers are increasingly aware of alternative driving options, and increasingly seriously considering them. Many U.S. policymakers are concerned about the environmental impacts of CVs, and have employed various policy instruments to encourage electric vehicle adoption. Most recently, President Biden expanded existing regulation on tailpipe pollution to boost sales of electric vehicles (Davenport, 2024). The transition to PEVs is therefore a relevant and pressing topic for both consumers and policymakers.

Figure 1: Although EVs were brought to market decades ago, sales of PEVs have increased rapidly in the United States over the past decade as consumers look to driving alternatives to CVs. (Data: International Energy Agency 2023)



One of the greatest challenges to widespread PEV adoption is installing adequate public charging infrastructure (Alanzani 2023). While the rate at which charging stations are being added is growing alongside the pool of PEVs, there are many PEVs relative to the number of charging stations and gas stations are far more common than charging stations. Given the convenience and reliability of operating a CV, many buyers find it difficult to justify the higher sticker price of a PEV (Rapson & Muehlegger 2023). Fortunately, policymakers in these states seem attuned to these concerns. The latest update from the Alternative Fuel Data Center (AFDC) indicates that there are 3,797 and 2,900 public (available and planned) charging stations in New York and Massachusetts, respectively (2024). According to historical data from the AFDC, these represent a 14% and a 21% increase in charging infrastructure since the end of 2022. In states like New York and Massachusetts which have prioritized expanding charging infrastructure yet still experience low PEV adoption compared to CV adoption, this paper answers the question: to what extent can charging station infrastructure influence drivers' decisions to adopt and use a PEV?

In order to understand why charging infrastructure matters for PEV adoption, we must consider the symbolic value of charging stations. Ease of accessibility to charging stations reduces the chances that the driver will fail to reach their destination because the vehicle ran out of charge, therefore they seem to represent safety and convenience on the road. Although most charging happens at home, owners of current electric vehicles cited shorter driving range and concerns about charging away from home as some of their greatest concerns prior to making their purchases. These concerns that the vehicle will run out of charge before reaching its destination (because the vehicle's range is shorter and more variable than the driver is used to or charging stations are too few and far between in an emergency, etc.) are known as "charge anxiety". In theory then, adding charging stations alleviates charge anxiety sufficiently for consumers to feel comfortable purchasing a PEV; however, White et al. (2022) find that charging stations predominantly increase adoption through a different treatment channel, namely by influencing consumer perceptions of their community's subjective norms regarding BEVs. The authors argue that extensive charging infrastructure represents greater social acceptance of electric vehicle drivers, which suggests that people generally perceive battery electric vehicles negatively in the absence of charging infrastructure.

Due to slow PEV adoption, there is limited publicly available data to investigate the extent to which charging station density affects PEV adoption. The most up-to-date and comprehensive publicly available source of data on electric vehicles is the National Household Transportation Survey, which surveys a relatively small nationally representative sample of electric vehicle drivers on their driving habits, vehicle characteristics, and demographics every five years. Various datasets on public charging station usage have recently been assembled (Baek et al., 2024; LeCroy & Dobbelaere, 2024); however, the Alternative Fuels Data Center (AFDC) maintains the largest and most current catalog of charging in the U.S.. To help bridge the gap in charging data and shed new light on the station usage of a small but potentially important subset of the charging station population, I assembled a station-level panel dataset tracking various measures related to PEV charging from charging stations on the campuses of higher education institutions (HEIs) in New York and Massachusetts. These states are also known for having many HEIs, therefore they are well-suited to study charging patterns at these institutions. I assembled the dataset by reaching out to colleges and universities which specified on their website that charging stations are available for PEV drivers on-campus. Despite efforts to follow up with schools, only 16 schools of the 44 schools I contacted showed interest in providing data, and only 12 schools responded with usable data (see Table 1. under III. Data Discussion for more details on each school).

Promoting social acceptance of environmentally friendly driving alternatives (like PEVs) is a unique selling point for many HEIs. In fact, Shields (2019) reveals they are often viewed as “catalysts” for sustainable development, therefore HEIs are plausibly adding charging stations to shape community opinion. This means that they may be affecting the amount and distribution of charging in the area independently of the community’s demand for charging; in other words, they are creating demand for charging electric vehicles on-campus by affecting consumer preferences for electric vehicles. Thus, I investigate the impact of adding charging stations to HEI campuses in New York and Massachusetts on PEV adoption and usage.

Under this assumption, I use a staggered differences-in-differences design to identify the marginal effect of adding a charging station on PEV adoption and charging station utilization on-campus. The treatment is therefore the addition of a charging station to campus. This design allows me to exploit the variation in the timing of station installations across campuses to estimate the effects of each additional station to a campus, holding all other factors (such as seasonal and across-campus differences in charging patterns) equal. I control for the historical price of electricity at home, which is where most charging happens, and changes in the pricing scheme used by the HEI.

Using a staggered differences-in-differences design, I show that HEIs can meaningfully impact PEV adoption and increase station utilization by adding charging infrastructure. Specifically, I find that adding the first station meaningfully increases station energy usage by anywhere between 22.4 kWh and 25.2 kWh daily, whereas each subsequent station meaningfully increases station utilization by anywhere between 5 kWh and 5.8 kWh daily. The number of unique users in a week significantly increased anywhere between 1 user and 1.7 users following the addition of the first station, and increased anywhere between 0.4 users and 0.5 users following the addition of subsequent stations. Notably, the number of repeat, unique users (i.e. PEV owners charging regularly on-campus) increased significantly both with the addition of the first station and subsequent stations. Overall, these findings suggest that the first station attracts a couple of PEV owners to charge on-campus, who charge their vehicles up to 125 kWh each week. For reference, the AFDC considers the average PEV battery capacity to be 54 kWh (although this can vary widely depending on model, temperature, battery age, etc.). On the other hand, subsequent stations attract less than one unique user each week, and encourage new and existing users to charge an additional 29 kWh each week. I also find there are diminishing marginal returns to both PEV adoption and station utilization from adding stations on-campus, which suggests that HEIs' capacity to encourage charging on-campus is constrained either by factors affecting demand for charging on-campus (e.g. congestion at charging stations and general parking) or consumer preferences for PEVs in the HEI community. Regardless, my findings suggest that there is growing demand for charging on-campus likely as a supplement for charging at home.

II. Literature Review

Partly due to slow adoption, there is little publicly available data on PEVs and charging station utilization, particularly in the U.S.. In the past few years, however, researchers seem to be paying more attention to electric vehicles, contributing to a growing body of literature on PEVs. I investigate relevant papers on the economics of PEVs and PEV charging, including papers that identify factors affecting PEV adoption and usage, papers identifying the key factors affecting charging station utilization, and papers making recommendations for electric vehicle policy. The final category seems the most developed, which makes sense given that many policymakers are passionate about facilitating the transition away from CVs, yet have been so far unsuccessful in considerably boosting PEV adoption.

In general, a consumer's choice to purchase a PEV depends on the net cost of a PEV, which carries a higher up-front cost (likely of a brand-new PEV as the used-PEV market is still immature) plus the cost of at-home charging and maintenance costs (which are low relative to CVs) minus federal and state rebates (Rapson & Muehlegger 2023). Electric vehicle buyers can receive up to $2,000 in New York or $6,000 in Massachusetts in rebates depending on the vehicle's range, along with up to $7,500 in rebates from the federal government legislated by the Inflation Reduction Act (U.S. News & World Report 2023). Rapson & Muehlegger (2023) affirm the importance of fuel cost savings in boosting electric vehicle adoption, and find that in New

York state, driving an electric vehicle could potentially save drivers between $202 and $258 per year, whereas annual savings range from $70 to $202 dollars in Massachusetts. An exhaustive literature review conducted by Pamidimukkala et al (2024) finds that the higher up-front cost, insufficient charging infrastructure, and shorter driving range relative to conventional vehicles are consumers' greatest concerns about purchasing an electric vehicle. On the other hand, they find that reducing air pollution and taking advantage of rebates are often cited as reasons for purchasing an electric vehicle. He et al. (2022) confirm that in Hong Kong, accessibility to charging and environmental concern meaningfully bolster consumer interest in purchasing a PEV, while shorter driving ranges reduce interest. Lashari et al. (2021) also show perceived environmental benefits and economic background to be the two strongest signifiers of electric vehicle adoption in South Korea. Both He et al. (2022) and Lashari et al. (2021) use stated preference survey data; however, Coffman et al. (2016) suggest that actual purchases of electric vehicles are much lower than stated preferences.

Certain demographics are associated with greater electric vehicle adoption, which I briefly discuss in order to appreciate the unequal distribution of the benefits of charging station infrastructure. In Ireland, Mukherjee & Ryan (2019) show that being located in an urban area is associated with greater early electric vehicle adoption, which is also higher among people with a university degree and lower among younger people (ages 19 to 24) and those renting their living space, which may indicate challenges to access to at-home charging infrastructure. Unsurprisingly, the higher cost of EVs and information asymmetry (i.e. people with a university degree are more likely to have encountered and researched an EV) creates barriers to adoption which are reflected in the demographic characteristics of the electric vehicle-owning population. Given that my primary dataset tracks the charging behavior of PEV owners on HEI campuses, it is reasonable to assume that the PEV owners in my sample are highly educated and own their own home.

Since PEV usage might be correlated with greater station utilization, I also investigate the factors influencing a driver's decision to use their PEV. Davis's (2023) analysis of the 2017 National Household Transportation Survey (NHTS) reveals that 89% of people who own an EV also own a CV, and 66% of households with a conventional vehicle drove their conventional vehicle more. Although I could not find any literature investigating the factors underscoring household substitution between their electric and conventional vehicles, there is some literature investigating the factors determining how much PEV owners drive and how they refuel. Nehiba (2023) finds that the cost of charging has a significant impact on New York BEV owners' decisions to drive, concluding that a 10 percent increase in residential electricity prices results in a 0.82 percent reduction in BEV mileage. Soltani-Sobh et al. (2017) affirm his conclusions at the national level. Furthermore, Nehiba also shows that electricity prices lose predictive power as public charging infrastructure expands, which suggests that people substitute public charging for at home charging as it becomes more convenient to charge at public stations. Contrary to findings on BEVs, Chakraborty et al. (2020) find that some PHEV owners in California rarely charge their PHEVs, instead refueling solely with gas.

Given that my primary dataset tracks charging station utilization on HEI campuses, it is also important to understand how drivers choose where to charge their vehicle and the factors influencing station utilization. A report on PEV owners in California suggests that drivers primarily choose where to charge their vehicle based on workplace charging availability and free charging (Tal et al., 2020). Additionally, they find that home ownership, type of house (e.g. multi-unit dwelling) and age of driver also influence where drivers charge. Furthermore, they discover that the choice of charging location may depend on technological factors like electric range. According to Borlaug et al. (2022), station utilization is determined by local PEV adoption, the size of the local charging network, and population density. Two case studies on station utilization at University of Georgia and Purdue University find that stations are most often occupied during the day and on weekdays (Hovet et al. 2018; Mathew et al. 2019). Typically, those charging their vehicles are faculty and staff, who have parking permits and for whom charging on-campus is more convenient because it is part of their daily activities (Mathew et al. 2019). At Purdue University, charge idling, where vehicles occupy a spot without charging, was found to account for up to 40 percent of occupied time depending on the station. At the University of Georgia, idling was also observed, but 90 percent of cars idled for less than one hour. These findings may suggest that poor charging practices like charge idling are endemic to HEI campuses and may contribute to congestion at charging stations.

Most papers on EV policy focus on quantifying the effect of consumer subsidies or the regressivity of a proposed tax on CVs. For example, Rapson & Muehlegger (2023) and Zhang et al. (2019), respectively, suggest that optimal EV policy includes subsidies to address market failures, such as local pollution, while Levinson (2019) suggests that a tax on gas is less regressive (meaning that lower income people disproportionately bear the financial burden of the policy) than regulating fuel economy standards. A gas tax should therefore reduce the adoption and usage of CVs in an equitable way, which may prompt more people to consider EVs by lowering their relative cost. The policy research most relevant for my paper; however, is whether or not expanding charging infrastructure affects EV adoption, since the goal of my paper is to determine if there is any benefit to college campuses increasing the number of charging stations on-campus. Li et al. (2017) estimate that indirect network effects leading to feedback loops between EVs and charging infrastructure contributed to the significant rise in adoption in response to the Inflation Reduction Act's $7,500 consumer rebate, but that the same subsidy applied to charging station deployment could have more than doubled EV adoption. Similarly, a cost-benefit analysis performed by NYSERDA (2019) found that the societal benefits of adding charging stations outweighed the costs in both Upstate New York and Long Island, but not Metro New York City due to high electricity costs. Ultimately, my contribution to the literature is to study how a different kind of policymaker, namely HEIs, might facilitate the transition to more sustainable and more energy secure methods of transportation through charging offerings on-campus.

III. Empirical Theses

To introduce my data and variables, it is useful to establish a theoretical framework to better understand the factors that feed into a PEV driver's decision to charge. The treatment effect, which will be station additions to a campus, primarily affects the choice to adopt and charge a PEV on-campus through three channels.

First, the extensive margin captures the impact of the first station to be added on-campus. Since I have historical data going back to each station's inception[1], I can assess the impact of introducing charging infrastructure on-campus on PEV adoption. The accuracy of these estimates is limited by my dataset, which only captures charging behavior on-campus. Since I can only count the vehicles which plugged into the charging station at some point, I cannot measure the number of PEVs on-campus before charging infrastructure was added. It is likely that those charging on-campus immediately following the introduction of charging stations on-campus

[1] with the exception of one station on Skidmore College campus that was owned by National Grid and later transferred to Skidmore

already owned a PEV and took advantage of the opportunity to charge on-campus. On the other hand, there is reason to believe that the presence of charging infrastructure may have a unique impact compared to adding additional charging stations, especially in light of White et al. (2022) who suggest that charging stations symbolize social acceptance of electric vehicles. This may indicate that even one station might have a larger impact on HEI community perception regarding PEVs, and thus reduce the possible social costs of adopting a PEV. Thus, I expect that having any stations on-campus can encourage PEV adoption in the long-term.

The intensive margin captures the impact of installing an additional charging station on-campus. Subsequent stations also have symbolic value, as according to White et al. (2022) more chargers are linked with greater PEV adoption, therefore I expect that adding additional charging stations will increase the number of unique users charging on-campus. While I believe this is the most likely scenario, it is also possible that PEV adoption is unaffected by subsequent station additions, either because the community still overwhelmingly prefers to drive a CV or because there is insufficient charging infrastructure to support additional PEVs. Campuses that have not possessed multiple stations for very long might be more susceptible to the former issue as both perceptions of PEVs take time to change and purchases of long-term investments like automobiles may not happen as soon as preferences change. Consequently, I believe that an increase in the number of unique users charging on-campus as more stations are added reflects recent purchases of PEVs rather than merely the decision to substitute charging on-campus for charging elsewhere.

Explaining the impact of the latter issue requires an understanding of congestion, which is the third channel through which adding charging stations affects PEV adoption. In the context of PEV charging, congestion is when PEV drivers "crowd out" one another. Congestion is likely to happen during peak charging times (i.e. during the work week and during the day) on campuses where there is a lot of demand for charging or bad charging practices. An example of bad charging practices might be charge idling, which is when the vehicle is fully charged yet still parked in the designated spot for charging. Other factors might contribute to congestion, such as the unreliability of subsequent stations (e.g. they require maintenance more often, so it is less likely that they will be able to deliver a charge when drivers need it). In theory, adding more (reliable) charging stations should relieve congestion; however, adding more stations might also create more demand for charging, which causes congestion. Thus, the impact of congestion on adoption is ambiguous. While I have no direct measure of congestion, I attempt to quantify the demand for charging on-campus by supplementing my results on the number of unique users charging on-campus with an investigation of the effect of charging infrastructure on station utilization.

IV. Data

My primary dataset is composed of per session charging data from each station on thirteen HEI campuses, ranging from May 5, 2014 to January 31, 2024. I received information on many different variables; however, the relevant ones for my analysis are the date and time of each charging session at each charging station, the electricity consumption per charging station (kWh) per session, and user ID numbers that uniquely identify each time a user charges their PEV. Using this data, I can identify the first time the first station is used (i.e. when did the campus go from having no charging infrastructure to having charging infrastructure?), the first time each subsequent station is used (i.e. when were subsequent stations added to campus?), and the last time each station is used (i.e. have any stations not been used for a while?).

Identifying the first time the first station was used indicates when charging infrastructure was added to the campus, while identifying the first time each subsequent station is used allows me to count how many stations are on a campus at a given time. My last treatment variable is a squared term for the number of stations on-campus, which allows for a nonlinear relationship between charging on-campus and PEV adoption. I expect that adoption will grow more slowly as the number of stations on-campus increases because there is likely a segment of the HEI community who are already particularly interested in owning a PEV and are sensitive to changes in the charging infrastructure on-campus, but as the charging needs of these drivers are met, it becomes harder to incentivize new people to adopt a PEV purely on the basis of charging on-campus. This is partly because there will always be some people for whom a CV is preferable, whether that be a function of its longer driving range, lower price, personal preference, or any other factor. Therefore, the number of users added by the tenth station is likely going to be fewer than the number added by the first or second stations, so the coefficient on the stations squared term should be negative.

I am primarily interested in the effect of these treatment variables on PEV adoption, which I proxy with the number of new, unique users in a week. Since each user is associated with a unique ID number, I can differentiate between repeat users and new users charging at a station. One limitation to using user IDs is that there is not always a user ID reported for every session. A fairly large share of observations were missing (42% of observations missing user IDs from the set of 161,278 observations). On the other hand, one of the advantages of using user IDs to measure PEV adoption is that I can draw conclusions about PEV adoption patterns without having to control for county, state, or nation-level trends in PEV adoption.

This also has important implications for my second dependent variable, namely daily station electricity consumption, which proxies station utilization. Station utilization is meant to supplement my results for adoption, as I would expect to see greater levels of station utilization as PEV adoption increases. Ideally, greater utilization reflects drivers' decisions to drive more; however, since I do not observe charging behavior at home or at other public locations, I cannot infer that drivers are not simply substituting charging elsewhere for charging on-campus. Still, an uptick in station electricity consumption indicates that PEV drivers want to charge on-campus, which might suggest that convenient and reliable charging infrastructure outside of the home is feasible.

I obtained data from twelve HEIs in New York and Massachusetts, which are listed in *Table 1*, along with the HEIs that responded without usable data and their reasons for doing so. For the HEIs that provided usable data, there is also information on the city in which the campus is located, the current number of stations, when charging infrastructure was first installed, the pricing scheme, details about any changes in the price of charging, and whether or not user IDs are reported.

The city in which the campus is located indicates that the HEIs in my dataset range from very rural settings, like Colgate University's campus, to suburban settings, like UMass Amherst's campus in Newton, and urban settings, like SUNY ESF. There are no HEIs with metropolitan settings, as I did not reach out to schools in metropolitan areas like New York City because transportation and charging patterns are likely to be different. I believe this to be the case because metropolitan areas are known for having reliable public transportation, high traffic, and parking shortages. Given these deterrents, adding charging stations may not have much of an impact on PEV adoption unless charging infrastructure increases significantly.

Table 1. Relevant Characteristics to Charging on HEI Campuses That Expressed Interest in Sharing Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HEIs	State	Respond with Usable Data?	City	First Time a Station Used	# of Stations	Pricing Scheme	Change in Price of Charging?	User IDs reported?
Colgate University	New York	Yes	Hamilton	19 Jun, 2014	3	First four hours are free, over four hours is $2 per hour	No	Yes
Cornell University	New York	Yes	Ithaca	24 Apr, 2018	7	Free	No	Yes
SUNY Buffalo	New York	Yes	Buffalo	15 Nov, 2019	18	$1.50 per hour	Yes, added an hourly fee ($1.50) in Aug 2021	Yes
SUNY ESF	New York	Yes	Syracuse	1 Sep, 2021	12	$0.20 per kWh	No	Yes
SUNY New Paltz	New York	Yes	New Paltz	3 Jan, 2015	13	$0.10 per kWh	Yes, changed rate structure from hourly fee to energy fee ($0.10 per kWh) in Apr 2016. Stations installed in summer of 2019 left free through Jan 2020, then added this energy fee	Yes
SUNY SCCC	New York	Yes	Schenectady	11 Aug, 2021	26	$0.35 per kWh	Yes, added energy fee ($0.25 per kWh) in Mar 2022, raised fee to $0.35 per kWh in Sep 2023	Yes
Skidmore College	New York	Yes	Saratoga Springs	13 Jun, 2017	14	$0.20 per kWh, over four hours is an extra $4 per hour	Yes, added an overstay fee ($4 per hour after 4 hours of charging for ChargePoint stations) in Nov 2022 and an energy fee ($0.20 per kWh) in Jan 2023	No
Syracuse University	New York	Yes	Syracuse	18 Apr, 2018	6	$0.20 per kWh	No	No
Union College	New York	Yes	Schenectady	29 Mar, 2019	22	$0.18 per kWh	No	Yes
University of Rochester	New York	Yes	Rochester	30 May, 2018	20	$1 per hour	No	Yes
Smith College	Massachusetts	Yes	Northampton	18 Jan, 2020	4	First two hours are free, over two hours is $0.50 per hour	No	Yes
UMass Amherst	Massachusetts	Yes	Amherst, Hadley, Newton	5 May, 2014	29	Charging club	Yes, "6-7 years ago" set up the UMass EV Charging Club, which is only available to drivers with a full year parking permit. If in the club, pay for the current cost of electricity ($0.18 per kWh as of May 16, 2023). Those not in the club pay this energy fee plus hourly fee ($1.60 as of July 1, 2023) (exception: Campus Center Parking Garage pay to park plus energy fee). After 30 min of completing charge, overstay fee ($9 per hour) applies	No
Amherst College	Massachusetts	No, do not collect data						
Stonehill College	Massachusetts	No, do not collect data						
University of Connecticut	Connecticut	No, data is periodically deleted and only collected from some charging stations						
Wesleyan University	Connecticut	No, only very recently (Oct 2023) started collecting data						

Notes: "SUNY" stands for "State University of New York". UMass Amherst has several campuses hence the multiple entries for "City". My original intention was to include HEIs in Connecticut as well; however, no HEIs in the state responded with usable data.

Table 2. Sample Summary Statistics

	(1) N	(2) mean	(3) median	(4) sd	(5) min	(6) max	(7) sum
Panel A. Weekly Number of Unique Users by Campus Variables							
Number of unique users	4,510	1.466	0	2.943	0	24	6,613
Number of unique, repeat users	4,510	0.835	0	1.806	0	19	3,764
Number of unique, repeat users, excluding years affected by COVID-19	3,844	0.846	0	1.852	0	19	3,252
Number of unique users, excluding summers and years affected by COVID-19	2,736	0.910	0	1.921	0	19	2,491
Charging infrastructure introduced	4,510	0.002	0	0.045	0	1	13
Number of charging stations	4,510	4.494	1	7.067	0	26	
Number of charging stations squared	4,510	70.120	1	151.536	0	676	
Panel B. Daily Energy Usage by Station Variables							
Electricity consumption (kWh)	595,028	2.794	0	10.957	0	300.955	1,662,381
Electricity consumption, excluding years affected by COVID-19	507,104	2.888	0	11.317	0	300.955	1,464,567
Electricity consumption, excluding summers and years affected by COVID-19	360,769	3.242	0	12.083	0	300.955	1,169,525
Charging infrastructure introduced	608,360	0.003	0	0.017	0	1	173
Number of charging stations	608,360	6.206	2	8.233	0	26	
Number of charging stations squared	608,360	106.302	4	182.532	0	676	
Panel C. Control Variables							
NY Monthly average price of residential electricity (in 2014 dollars)	117	22.943	22.812	1.345	20.381	27.198	
MA Monthly average price of residential electricity (in 2014 dollars)	117	26.303	26.099	2.218	21.123	33.590	

Note: I consider years affected by COVID-19 to be the week beginning March 2nd, 2020 until the week ending August 2nd, 2021.

Panel A. and *Panel B.* provide summary statistics for the variables relevant to the estimation of the weekly number of unique users on a campus and the estimation of the daily amount of energy usage by a station, respectively. *Panel A*. indicates there are at most 173 stations across 13 campuses. I drop one station which was used very few times compared to the other stations in my sample (<50 sessions recorded). For UMass Amherst, I grouped together the Amherst and Hadley campuses since they are close to one another and considered the Newton-campus separately since it is a several hour drive from the Amherst and Hadley campuses. Starting with my treatment at the extensive margin, *Table 1.* indicates that the dataset includes HEIs that were early adopters of charging infrastructure, like SUNY New Paltz, and those that more recently adopted charging infrastructure, like Smith College. *Table 1.* also breaks down the number of stations by HEI, ranging from just three stations to 29 stations, with a considerable amount of variation in between these extremes. Thus, I am able to assess the impact of having only a few stations on-campus and the impact of having many stations on-campus, which is one of my alternative specifications in which I bin observations based on the number of stations on-campus.

When reaching out to HEIs, I also asked if the price of charging on-campus has ever changed. An increase in the price of charging (e.g. adding an overstay fee, which charges drivers extra for every hour they leave their car plugged in after charging is complete) might disincentive charging on-campus (as long as charging elsewhere is still relatively more expensive). Thus, I would expect both station utilization and PEV adoption to decline as the price of charging rises. In order to control for pricing changes, I include a campus-by-price-change fixed effect, which is equal to one for all observations if a campus has not changed their pricing scheme, equal to two for all observations after the first change in the pricing scheme, equal to three for all observations after the second change in the pricing scheme, and so on. Five schools changed their pricing scheme at some point, which are shown in *Table 1*.

Lastly, *Table 1.* indicates which schools reported user ID numbers. Nine HEIs reported user ID numbers, for a total of 4,510 observations. According to Panel A. in *Table 2.*, there is an average of 1.47 unique users charging on-campus each week and a median of zero users. This suggests that the distribution of unique users is skewed to the right, meaning that most weeks there are few to none unique users and a few weeks for which there were many unique users. After dropping users who only charged on-campus once, the mean falls to 0.84 unique users. I hypothesize that dropping sessions that occurred during the COVID-19 lockdowns and dropping sessions that occur during summer and winter breaks will result in a higher average and median number of unique users. *Panel A* reveals that the average number of unique, repeat users increases to 0.85 after dropping observations affected by COVID-19 travel disruptions and increases further to 0.91 unique, repeat users after dropping observations that did not occur during the academic year. The median is not affected, which suggests that there are still some weeks in which many more users charge on-campus compared to others. I explore possible explanations for this phenomenon in the Results.

Overall, there are 6,613 unique users reported by the end of January 2024. Out of these, 6,180 were reported in New York as only one HEI (Smith College) in Massachusetts reported unique users. To help put this number into perspective, I also obtained state-level micro-data on electric vehicle registrations in New York from 2017 to 2021. Registration data indicates that there were 29,333 electric vehicles registered by the end of 2021. In the context of the registration data, my data suggests that nearly a fifth of the PEVs registered in New York state charged at an HEI charging station. While not a large share, this only considers the few HEIs in my sample, therefore my count is likely an underestimate of the number of PEVs charging at HEI campuses. This suggests that HEIs play a not insignificant role in encouraging PEV adoption.

One case provides particularly strong evidence that HEIs are crucial players in PEV adoption. SUNY Buffalo added three stations initially, then added fifteen stations within a few months. *Figure 1.* provides strong suggestive evidence that charging infrastructure increases PEV adoption: the number of monthly unique users increases from a handful when there were three stations on-campus to more than 30 users after an additional fifteen stations are added. *Figure 1.* also indicates that there are almost half as many unique users during the summer months and winter break, which is consistent with my findings in *Table 2.*

According to Panel B. in *Table 2*, the mean daily energy usage for each station is 2.79 kWh, and the median is zero. This also suggests that distribution of energy usage is skewed to the right, therefore there are many days where stations are not used and several days where stations drained a lot of energy, up to 301 kWh. *Figure 2.* also provides evidence that stations were utilized much more after the additional fifteen stations were added, as monthly total energy usage jumps from less than 500 kWh daily to more than 8,000 kWh. Similar to *Figure 1.*, station utilization peaks during the academic year and is nearly half of those levels during breaks. As expected, the mean is higher when dropping observations affected by COVID-19 travel disruptions (2.89 kWh) and even higher when dropping sessions that did not occur in the academic year. Overall, over 1.66 million kWh were drained from stations across all HEIs in my sample. Finally, I point out that there are many more observations for the treatment variables than for daily station energy usage because the treatment variables are calculated at the campus level. I do this because I still know how many stations are on-campus using energy usage data from other stations if a given station was last used some time ago.

Finally, I have included summary statistics for my control variable: monthly residential electricity prices, which I downloaded from the EIA. These prices were nominal, and later adjusted for inflation using the CPI: Urban Consumers All Items in the U.S. Electricity prices are similar across states although slightly higher for Massachusetts, which suggests that it is slightly more expensive to charge at home in Massachusetts.

Figure 1: The weekly number of unique users on SUNY Buffalo's campus increased more than five-fold after an additional fifteen stations were added to campus.

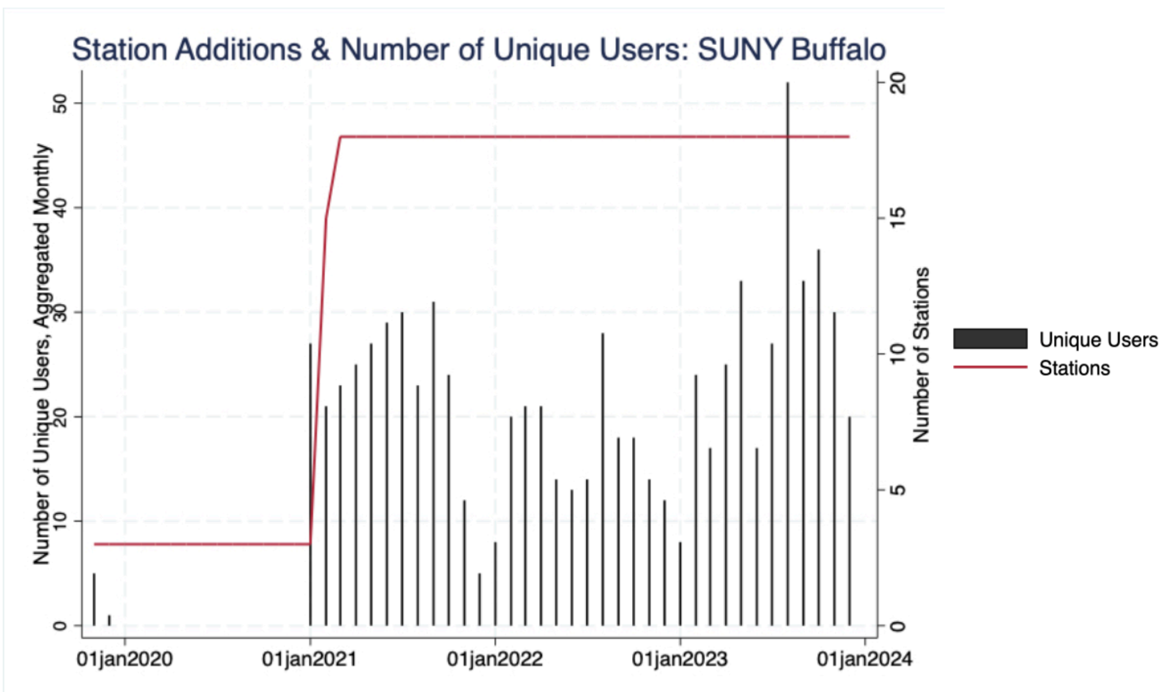
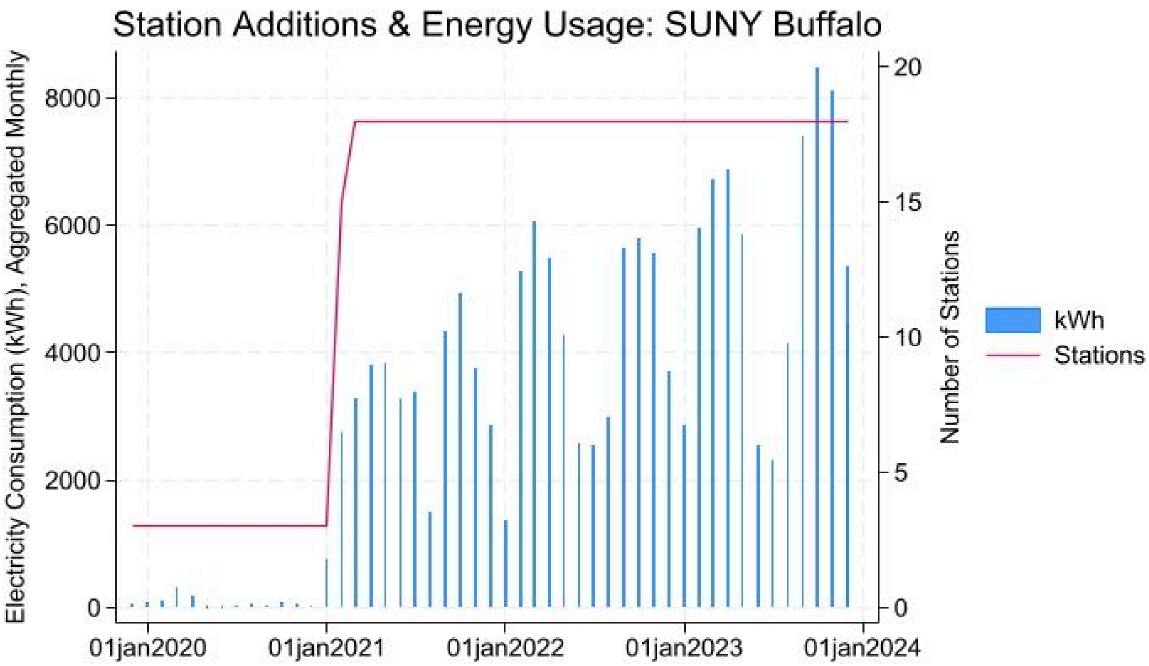


Figure 2: Daily energy usage per station on SUNY Buffalo's campus increased more than ten-fold after an additional fifteen stations were added to campus.



V. Methodology

I use a staggered differences-in-differences design to gain insight into whether or not HEI campus charging infrastructure can affect PEV adoption among users that choose to charge on-campus. To do so, I will be running logit which censors observations for the number of unique users and energy usage that are below zero. My main model is represented by the following two equations:

$$NumberofUniqueUsers_{it} = \beta_1 Any\_stations + \beta_2 Station\_obs + \beta_3 Station\_obs\_squared + \theta X_{it} + \delta_t + \delta_i + \varepsilon_{it} \quad (1)$$

$$EnergyUsage_{it} = \beta_1 Any\_stations + \beta_2 Station\_obs + \beta_3 Station\_obs\_squared + \theta X_{it} + \delta_t + \delta_i + \varepsilon_{it} \quad (2)$$

On the left side of the equation, I have two empirical specifications. First, I will estimate the effect of the treatment variables– Any_station, Station_obs, and Station_obs_squared– on the number of unique users at the campus level, which will be aggregated by week, as indicated by equation (1). I will also estimate the treatment effect on the daily amount of energy usage at the station level to capture station utilization, as indicated by equation (2). On the right side of the equation, both empirical specifications share the same treatment variables. They also share the same control variable, which is indicated by X_{it}. As mentioned in the Data section, I anticipate that rises in the price of residential electricity, which proxies the cost of at-home charging, may discourage drivers' from adopting a PEV and encourage existing PEV owners to charge more on-campus, therefore I control for monthly variation in residential electricity prices at the state-level in my specification.

Both specifications also include week of sample and year fixed effects (δ_t). Week of year fixed effects should capture weekly trends in PEV adoption, such as seasonal trends in car-buying and times when there are more visitors on-campus who might be charging on-campus for the first time. I also included a year fixed effect to capture long-term trends in new users charging on-campus. These trends include differences in car-buying from year to year, and differences in the choice of charging location from year to year, perhaps due to long-term construction which blocks access to chargers or travel disruptions due to the COVID-19 pandemic. With regards to COVID-19, I expect it will also be necessary to drop all observations during which COVID-19 necessitated that learning shift to a virtual format, disrupting commuting to campus well into 2021.

It is also important for my second specification to capture weekly trends in charging, such as losses in battery capacity during the winter (which might increase energy needed) or commuting differences due to the academic calendar (which might decrease charging on-campus). Cold temperatures can reduce driving range by about 25% (Bartlett & Shenhar 2023), therefore controlling for battery loss ensures that my estimates of energy usage are not biased upwards. Year fixed effects should account for long-term changes in charging behavior, such as reductions in battery capacity as the vehicle ages. Ideally, I would have full time fixed effects for equation (1), which includes day of week and within-day fixed effects; however, my most granular fixed effect is Weekday fixed effects, which captures differences over time in station energy usage on weekends compared to weekends. Energy usage is lower on average during the weekends than during weekdays (see Appendix *Figure 1*), which makes sense given that most PEV owners charging on-campus work there and most people do not work on the weekends. Hence, they have no reason to visit campus and would likely incur much inconvenience by driving to campus to charge, unless they live close to campus.

Lastly, I include campus-by-price-change fixed effects in my first estimation to capture differences across campuses in factors affecting charging behavior (e.g. size of the local charging network), as well as charging trends within campuses before and after the pricing scheme changes. Since energy usage is estimated at the station level, I include both campus-by-price change fixed effects and station fixed effects. Station fixed effects account for differences between the popularity of the stations depending on their location, reliability (i.e. how often do they require maintenance?).

Lastly, ε_{it} represents errors across weeks for each campus for the first specification, and errors across days for each station for the second specification.

VI. Results & Discussion

Table 1. presents the results of my primary empirical specification, which estimates the effect of having stations on-campus on the number of unique users in a week. Since the number of unique users proxies PEV adoption and PEV adoption has been shown to be positively associated with perceived charging station accessibility, I would expect small, positive coefficients for “Any stations” and “Station observations”. I expect adding the first station to have a small impact because users are likely existing PEV owners who substitute charging at-home for charging on-campus. Similarly, I expect adding subsequent stations does not have a large effect because automobiles are a big investment which usually only happens after their current vehicle is due to be replaced. Additionally, those interested in purchasing a PEV might perceive a significant amount of congestion with only a few charging stations on-campus and are therefore waiting for additional stations to be added. As expected, the coefficients for both treatment variables are small, positive, and statistically significant across nearly all estimations.

The coefficient for “Any stations” in my Main (1) and Clustering Standard Errors By Campus (2) estimations suggests that having any charging infrastructure on-campus attracts 1.212 unique users each week and 1.033 repeat, unique users each week. Adding back COVID-19 years (4) raises the estimate of unique users slightly, which indicates there might have been a few users charging on-campus for the first time during COVID-19. Using calendar time fixed effects instead of sample time fixed effects increases the precision of my estimates and results in a slightly larger coefficient of 1.729 unique users each week which is statistically significant at the 1% level.

I find that each additional station increases the number of unique users charging on-campus each week by 0.526 (1), (2); however, this result loses significance after clustering standard errors (2). On the other hand, each additional station increases the number of unique, repeat users by 0.393, which is statistically significant at the 1% level even after clustering standard errors (3). Running tobit on the full dataset reveals that each additional station increases the number of unique users by 0.448. Since some schools added stations during COVID-19, it is

	Weekly Unique Users on Each Campus						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Unique Users	Main	Clustering Standard Errors by Campus	Repeat Unique Users Only	Adding Back COVID-19 Years	Using Calendar Time FE	Including Station Subtractions	Binning Stations
Charging infrastructure introduced	1.212*	1.212**	1.033**	1.256*	1.729***	1.197*	
	(0.663)	(0.505)	(0.447)	(0.651)	(0.658)	(0.664)	
Number of charging stations	0.526***	0.526	0.393***	0.448***	0.447***	0.528***	
	(0.035)	(0.321)	(0.024)	(0.029)	(0.030)	(0.035)	
Number of charging stations squared	-0.019***	-0.019	-0.016***	-0.016***	-0.016***	-0.020***	
	(0.002)	(0.015)	(0.001)	(0.001)	(0.001)	(0.002)	
Station subtracted						0.846	
						(1.412)	
Monthly average price of residential electricity	-0.106***	-0.106	-0.064***	-0.109***	-0.108***	-0.112***	-0.102
	(0.032)	(0.084)	(0.022)	(0.030)	(0.027)	(0.032)	(0.147)
bin_2: 1 to 3 stations							20.578***
							(1.866)
bin_3: 4 to 10 stations							21.791***
							(2.328)
bin_4: 11 to 19 stations							22.868***
							(2.421)
bin_5: 20+ stations							27.420***
							(2.584)
Includes COVID-19 years	No	No	No	Yes	No	No	No
Campus-by-price-change FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of sample, week of sample FEs	Yes	Yes	Yes	Yes	No	Yes	Yes
Observations	3,825	3,825	3,825	4,491	4,491	3,825	3,825

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

likely that these results overestimate the true number of unique users charging on-campus. I also conduct a robustness check which adjusts the number of stations on-campus if a station has not been used for more than a year, as this might indicate that the station is no longer operable or inaccessible. Including these so-called "station subtractions" (6) barely alters the coefficient and increases its significance. Since only three stations in the sample that provided user ID data are subtracted, it is also possible that there simply were not enough apparent station subtractions to capture the full effect of station subtractions. This is likely, given that the coefficient on station subtractions (an indicator variable which is equal to 1 in the week for which campuses removed stations) is statistically insignificant. Notably, this coefficient is positive, which is contrary to expectations.

The squared term for the number of stations ranges from -0.016 to -0.020 unique users each week and is statistically significant at the 1% level in every estimation except (2). This suggests that the number of unique users each week increases at a decreasing rate as the number of stations on-campus grows. This makes sense given that I would not expect the 20th station to impact a driver's perception of charging station accessibility on-campus as much as the 5th station, unless stations are very congested even for a large number of stations on-campus. Consequently, I expect that each additional station attracts fewer unique users compared to the previous station. Ultimately, these results suggest that adding charging infrastructure on-campus induces existing PEV owners to charge on-campus, while expanding charging infrastructure has a very small, yet significant, impact on PEV adoption.

Another way I try to capture the effect of charging stations on unique users charging on-campus is by binning stations (7). The first bin is for zero stations, the second is for one to three stations, the third is for four to 10 stations, the fourth is for 11 to 19 stations, and the fifth is for more than 20 stations. Since I drop the first bin, I interpret the coefficients on the second bin as the following: compared to having no stations, having one to three stations increases the number of unique users by 20.578. Similarly, having four to 10 stations adds 21.791 unique users compared to having no stations, having 11 to 19 stations adds 22.868 unique users compared to having no stations, and having more than 20 stations adds 27.420 unique users compared to having no stations. These results are statistically significant with a confidence level of 99%. While the number of unique users added in each bin is about the same for the first three bins, the last bin holds nearly five more unique users compared to the other bins. Since there does not seem to be any clear correlation between the number of charging stations and the time since charging infrastructure was introduced, it is unlikely that these results suggest that PEV owners are slow to respond to charging station infrastructure. It is more plausible that there are more unique users in the last bin because one of the two HEIs in my sample with more than 20 stations (i.e. University of Rochester) also happens to be a very large school, which increases the potential number of PEV owners who are likely to charge on-campus.

Residential electricity prices have a very small negative impact on the number of unique users on-campus which is statistically zero when clustering standard errors (2) or binning stations (7). I believe that PEV adoption is negatively correlated with the cost of at-home charging because most charging happens at home (DOE, 2023), so drivers are more likely to put off purchasing a PEV if the price of charging at-home rises a lot. Consequently, there will be fewer unique users charging on-campus compared to previous weeks. My results are not surprising given that electricity prices are measured at the state-level; however, electricity prices can vary widely between counties. Thus, measurement error in electricity prices likely biases my estimates towards zero. Unfortunately, the EIA does not provide more granular data than what I have.

Table 2. presents the results of my secondary empirical specification, which estimates the effect of having stations on-campus on daily station energy usage (kWh). Since energy usage proxies station utilization and PEV adoption was just shown to increase as charging infrastructure expands, I also expect positive coefficients for "Any stations" and "Station observations". The magnitude of these coefficients depends on how much each driver is charging, which may be affected by congestion and the existing charge on the vehicle.

The coefficients for "Any stations" and "Station observations" are positive across all estimations, which indicates that station energy usage rises when charging infrastructure is added. Specifically, adding the first station increases daily energy usage by 24.196 kWh in my Main (1) and Clustering Standard Errors By Campus (2) estimations, which is roughly the same across all estimations. These results are always significant with a confidence level of 99%. This suggests that the first few users on-campus are draining a lot of energy from the station. Each subsequent station increases energy usage by 4.966 kWh daily, which is statistically significant with a confidence level of 99% across all estimations. Since the number of unique users on campus is also rising as stations are added, these results suggest that PEV owners charging on-campus after subsequent stations are added are using less energy than the first couple of PEV owners charging at the first station. Three campuses in the sample of HEIs that provided energy usage data removed stations at some point: University of Rochester, SUNY SCCC, and UMass Amherst (Amherst & Hadley). Including an additional variable to capture the effect of station subtractions on station energy usage (5) indicates that removing a station decreases energy usage by 2.666 kWh each day. I expect that removing stations reduces charging at a station, therefore this aligns with my expectations although these findings are not statistically significant as only five stations were subtracted. Earlier, I found that removing a station slightly increased the number of unique users. In comparison to the results for "Station subtractions" in the unique user estimation, the result for energy usage is plausible: removing a station reduces congestion levels over time by discouraging some people from purchasing a PEV (or encouraging them to postpone the purchase) and discouraging existing PEV owners from charging on-campus. This only makes sense if the station is no longer accessible or rendered inoperable, thus I assume this is what happened since I was not informed that any stations had ever been taken offline when collecting my data.

As with the coefficients on "Station observations squared" for the unique users specification, the coefficients on "Station observations squared" are negative and statistically significant at the 99% confidence level across all estimations of energy usage. Every additional station increases energy usage by less than two-tenths of a kWh less than the previous station. Thus, both the number of unique users on-campus and charging station utilization rise more slowly as the number of charging stations on-campus rises.

The results of binning stations in the same way as for the unique users estimations (6) indicates that compared to having no stations, having one to three stations increases energy usage by 177.273 kWh. Similarly, having four to 10 stations drains about 188.392 kWh compared to having no stations, having 11 to 19 stations drains about 193.796 kWh compared to having no stations, and having more than 20 stations drains about 199.020 kWh compared to having no stations. These results are statistically significant with a confidence level of 99%. Each bin of stations drains more energy compared to the previous bin, but by a lesser amount compared to the previous bin (e.g. bin 11 drains eight more kWh than bin 2, bin 4 drains five more kWh than bin 3, and bin 5 drains five more kWh than bin 4). This suggests that campuses with more stations are probably being utilized more than campuses with fewer stations because there is greater perceived and actual charging station accessibility (i.e. less congestion), which allows PEV owners to charge more. In the context of the results of binning stations on the number of unique users, these results support the conclusion that the new users on campus are able to utilize the stations on-campus.

Table 2. Daily Energy Usage at Each Station

Electricity Consumption (kWh)	(1) Main	(2) Clustering Standard Errors by Campus	(3) Adding back COVID-19 years	(4) Using Calendar Time Fixed Effects	(5) Including Station Subtractions	(6) Binning Stations
Charging infrastructure introduced	24.196*** (4.515)	24.196*** (3.662)	22.382*** (3.674)	21.942*** (3.607)	25.200*** (3.747)	
Number of charging stations	4.966*** (0.088)	4.966*** (1.060)	5.777*** (1.203)	5.175*** (1.124)	5.138*** (1.087)	
Number of charging stations squared	-0.161*** (0.003)	-0.161*** (0.033)	-0.180*** (0.035)	-0.167*** (0.035)	-0.157*** (0.031)	
Station subtracted					-2.666 (5.039)	
Monthly average price of residential electricity	0.333*** (0.081)	0.333 (0.520)	0.458 (0.424)	0.435 (0.527)	0.437 (0.472)	0.085 (0.340)
bin_2: 1 to 3 stations						177.273*** (9.319)
bin_3: 4 to 10 stations						188.392*** (12.641)
bin_4: 11 to 19 stations						193.796*** (13.256)
bin_5: 20+ stations						199.020*** (15.906)
Includes COVID-19 years	No	No	Yes	No	No	No
Station, campus-by-price-change FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year of sample, week of sample, weekday FEs	Yes	Yes	Yes	No	Yes	Yes
Observations	507,088	507,088	595,012	507,088	505,208	507,088

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, these results suggest that the first station brings a few PEV users to campus who are able to charge their vehicle longer because there is not a lot of demand on-campus for charging. As subsequent stations are added, more drivers are incentivized to adopt a PEV and charge it on-campus which increases congestion. In reaction to greater demand for charging on-campus, drivers charge less. Alternatively, the fuel economy of PEVs may simply have improved since the first charging station was added on-campus. For several HEIs in my sample (e.g. UMass Amherst), charging infrastructure has existed for more than 10 years. It is not difficult to imagine that vehicles have simply become more efficient, which considerably reduces the need for charging.

Finally, I consider the implications of my control variable, residential electricity prices. I would expect that charging station utilization on-campus would increase as charging at home becomes relatively more expensive (as long as charging on-campus does not depend on energy prices). Electricity prices are statistically significant only for the Main (1) estimation; for all subsequent estimations, a one dollar increase in the price of electricity has statistically zero impact on charging station utilization. Unlike the results of estimation (6) in *Table 1.,* binning stations result in a positive electricity price coefficient, which is likely because owners are substituting charging at-home for charging on-campus.

VI. Conclusion & Policy Implications

Over the past few months, I have compiled charging station data from HEIs throughout New York and Massachusetts to understand their role as catalysts for developments in sustainability. I ultimately received usable data from 13 HEIs to investigate the extent to which these institutions can impact PEV adoption through charging infrastructure on-campus. I supplement these findings with an investigation of the impact of charging infrastructure on station energy usage, which captures differences between stations in utilization. I anticipate that adding charging infrastructure will affect PEV adoption and station utilization at the extensive margin, which is the impact of adding the first station, and at the intensive margin, which is the impact of adding subsequent stations. Additionally, I consider the implications of congestion, which I cannot directly measure, on PEV adoption and station utilization. Using a staggered differences-in-differences design, I show that HEIs can meaningfully impact PEV adoption by adding charging infrastructure. Specifically, I find that adding the first station meaningfully increases station energy usage by about 24.2 kWh daily, whereas adding subsequent stations meaningfully increases the number of unique users in a week by less than one and increases the amount of energy used by each station by about five kWh each day. I also find there are diminishing marginal returns to both PEV adoption and station utilization from adding stations on-campus, which is likely achieved when campuses install sufficient charging infrastructure to meet current demand for charging. Since the average battery capacity of a PEV is around 50 kWh, these results suggest that PEV users treat charging on-campus as a convenient supplementary source of charging, rather than the main source of charging, which still likely happens at home.

In general, my results suggest that HEIs can catalyze PEV adoption through charging on-campus, although this effect shrinks as the number of charging stations exceeds current demand. I believe that HEIs should consider the number of stations already on campus when deciding whether or not to install additional charging stations. I also advise taking steps to gauge how much interest the community has in adopting PEVs, such as a transportation survey.

My empirical methodology is limited in several ways by my data. Most obviously, I only have 13 HEIs in my sample, and only nine reported user IDs that distinguish one user from another. Additionally, I only received data from two schools in Massachusetts (which translates to three campuses). This may limit the generalizability of my results outside of New York state, in which most of the HEIs were located. Regardless, I believe that my results can generalize to most areas in the Northeast, given that the campus settings in my sample range from rural to urban (but exclude metropolitan) and that PEV adoption and charging infrastructure is largely comparable. I was also limited by the data I could find on residential electricity prices, which captured differences in the average price between states.

In the future, I would like to explore several related tracks. First, I considered controlling for the price of gas in my estimations; however, there was little literature or surveys that indicated PEV drivers were actively switching between different types of fuel and vehicles depending on the cost of refueling each. What I did find suggested that there was no causal relationship; however, investigating this further might prove useful for policymakers looking to minimize our carbon footprint by reducing demand for gas. Although my dataset does not provide information on the specific model charged at each station, I would also expect heterogeneous effects of adding charging infrastructure on-campus on BEV station utilization versus PHEV station utilization. BEVs might be more sensitive to charging station infrastructure since they rely completely on it than PHEVs, therefore I might expect BEV adoption to increase more in response to PHEV adoption; however, my results suggest that charging on-campus is likely not the main source of charging for most users, so there might not be any difference. Regardless, understanding trends in BEV and PHEV adoption on-campus might be valuable to HEI policymakers as they seek to make decisions that minimize the community's impact on the environment. Finally, I would also like to explore the effect of adding charging infrastructure to campuses in metropolitan areas, like New York City or Boston. I did not reach out to HEIs in these areas because I anticipate that PEV adoption trends and charging patterns are likely much different in high-traffic areas with reliable public transportation compared to areas like Upstate New York, where most people rely on having a vehicle which they can refuel to move around. I anticipate that charging infrastructure likely does not have as much of an impact on PEV adoption, partly due to alternative transportation methods which are more environmentally friendly than driving (e.g. buses, subway) and partly due to crowded parking spaces, which might translate to greater congestion at the few charging stations available.

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Appendix

Figure 1. Investigating variation in the average daily energy usage per station for days of week to determine whether there is sufficient variation to be able to run day of sample fixed effects.