Electric Vehicle Charging at the Workplace: Experimental Evidence on Incentives and Environmental Nudges

Teevrat Garg Ryan Hanna Jeffrey Myers
Sebastian Tebbe David G. Victor*

March 23, 2024

Abstract

To minimize the environmental impact of electric vehicles (EVs) and support decarbonizing electric grids, drivers must charge their EVs when renewable energy generation is abundant. To induce a shift in charging behavior toward daytime hours with abundant solar energy, we conducted a field experiment ($n = 629$) at a large university campus to measure the influence of informational and financial incentives on the usage and timing of workplace charging. While neither intervention affected total charging, they induced opposite temporal shifts. Receiving information about the climate benefits of daytime charging induced a transition from early to later morning charging, whereas receiving larger financial incentives to charge on campus prompted a shift from daytime to overnight and early morning charging. We identify the quality of the charging network, incentive-induced scarcity concerns, and driver demographics as mechanisms behind the temporal shifts in charging.

*Garg: School of Global Policy and Strategy, University of California San Diego (teevrat@ucsd.edu); Hanna: Center for Energy Research, University of California San Diego (rehanna@ucsd.edu); Myers: School of Global Policy and Strategy, University of California San Diego (jmyers@ucsd.edu). Tebbe: School of Global Policy and Strategy, University of California San Diego (ytebbe@ucsd.edu); Victor: School of Global Policy and Strategy, University of California San Diego (david.victor@ucsd.edu). We want to thank Nicolas Astier, Josh Kavanagh, Byron Washom, Jan Kleissl, and Wente Zeng for helpful comments and suggestions; Emily Carlton and Jarrett Valdez for support with creating UCSD's EV charging club; Taylor Kempf, Yi-An Chen, and Avik Ghosh for data support; and Cypress Hansen for graphics. Funding for this research was provided by the National Science Foundation, TotalEnergies, and the Electric Power Research Institute, a nonprofit R&D organization focused on the electric power sector.

I Introduction

Every credible plan for deep reductions in greenhouse gas emissions that cause climate change involves the widespread electrification of light-duty transportation (International Energy Agency, 2021). Currently, electric vehicles (EVs) make up 7–24% of passenger vehicle sales in the three largest markets, China, the E.U., and the U.S., and these jurisdictions have set ambitious targets of 50-100% sales by 2030–2035 (European Environment Agency, 2021; Office of the Press Secretary, 2021; Executive Department State of California, 2020). Alongside the transition to EVs, most strategies for deep decarbonization anticipate a rapid uptake of renewable energy in the power sector (International Energy Agency, 2021), given that the carbon footprint associated with EV charging is contingent upon the carbon intensity of the power grid. The efficacy of these strategies hinges on the charging behavior of drivers, as charging directly affects both the power grid, which must accommodate increased demand, and emissions, given the fluctuating marginal emissions of renewable grids throughout the day. In solar-dominant grids, that variation puts a premium on midday charging when most people are at work.

Although most charging today is done at home — enabled because early EV adopters tend to be wealthier and have higher rates of homeownership (LaMonaca & Ryan, 2022) — workplace charging remains crucially important for two reasons. First, it is expected that future EV owners will have less access to private home charging and hence require alternative charging options. Second, as the electric grid moves toward renewable energy, the value of storage and flexible load options (like EV charging) will grow alongside the need to balance fluctuations in energy supply and demand. With many institutions, including corporations, public entities, and universities, committing to net-zero carbon goals and supporting their employees with workplace charging facilities, the extent to which EVs support deep decarbonization will depend on how drivers interact with workplace EV networks and how workplace policies influence their charging decisions.

In this paper, we run a series of interventions aimed at increasing workplace daytime charging and thereby reducing CO_2 emissions associated with charging. Drivers have various charging options (at campus, in public, or at home, if available) and charging habits that may be ingrained or flexible. We conducted a field experiment ($n = 629$) at the University of California San Diego (UCSD) campus — host to one of the world's largest workplace EV charging networks — to study how interventions shape drivers' decisions to use campus charging (i.e., to shift from off-campus to campus charging) and to alter when they charge. Our research, the first to measure the influence of interventions on workplace charging behavior, revolves around a newly established EV charging club for UCSD affiliates, which we created to collect data on drivers' demographics, vehicles, commuting and charging habits, and campus charge sessions.

Our experiment investigates how informational nudges and financial incentives can induce a shift in *where* and *when* drivers' charge. First, we provide drivers with information about the CO_2 emission benefits associated with daytime versus nighttime charging. Second, we give drivers discounts on campus charging irrespective of time. In the first phase of this financial treatment, participants receive either a small ($\$.16/kWh$) or large ($\$.23/kWh$) discount on the base campus rate of $\$.30/kWh$, such that campus charging is at least slightly cheaper than overnight home charging and equal to the average locational marginal price of electricity, respectively.[1] In the second phase of financial treatment, we retain half of the drivers on the large discount while moving the other half to the small discount to investigate habit formation for campus charging.

The environmental nudges about the climate benefits of daytime charging and campus charging discounts did not significantly increase total campus charging. We measure each individual's total campus charging via seven outcomes: the share of charging done on campus, the number of charging sessions, energy consumption, session cost, session duration, charge duration, and idle duration. These results imply that informational prompts and financial discounts did not induce a short-term shift to campus charging, suggesting that other strategies may be necessary to induce significant changes in charging behavior, particularly a shift in charging from home to the workplace. Our interventions led to a redistribution of charging sessions among commuter groups, particularly shifting sessions from high- to low-utilization garages, suggesting that informational nudges may have a more significant impact on workplace charging facilities characterized by lower congestion.

Although our interventions did not influence total campus charging, they led to significant shifts in the timing of campus charging sessions. We consider the timing, i.e., when a driver plugs in to charge, across five distinct windows: early morning (5–7), morning (7–10), midday (10–16), evening (16–21), and overnight (21–5). Receiving informational prompts about the climate benefits of daytime charging was associated with a 67% reduction in early morning charging and a shift to later morning charging, suggesting an intertemporal substitution toward daytime hours with higher renewable energy generation. Conversely, discounts on campus charging led to a 103% increase in overnight charging and a 61% increase in early morning charging, while charging decreased during the rest of the day. This indicates an intertemporal substitution in the opposite direction, away from midday solar energy generation, a perverse effect in which financial incentives for charging increase CO_2 emissions.

[1] The lowest-cost residential utility rate is $\$.145/kWh$, and the mean locational marginal electricity price for UCSD in October 2022 was $\$.07/kWh$.

Given an average of .89 weekly campus charging sessions per driver, incentives shifted the timing of 15–26% of all charging sessions.

Additionally, the second phase of the financial discount resulted in an 88% increase in evening sessions but less of a shift to early morning charging. The shift to evening charging may indicate that commuters adapted their routines to charge during periods with lower network utilization, i.e. to periods when a greater number of chargers are reliably available. The reduced shift to early morning may reflect less competition for chargers later in the morning, since fewer participants receive a large discount during the second financial discount (one-third of participants moved from the large discount to small). The interventions prompted a slight increase in charging by commuters experiencing low glitch rates during the second financial discount, indicating that financial incentives have stronger effects at workplace charging facilities characterized with greater reliability.

Next, we analyze the mechanisms driving temporal shifts in campus charging, focusing on three key factors: the quality of campus charging infrastructure, the experimental incentive structure, and driver characteristics. Understanding these mechanisms is crucial for institutions and policymakers to predict charging behavior changes and effectively target interventions. Specifically, the temporal shifts during the financial discount stem from drivers who charge predominantly in garages with high utilization and charger reliability (i.e., low rates of sessions that fail to initiate), suggesting that financial incentives have stronger temporal effects when drivers perceive charging facilities to be available and reliable.[2]

In addition to network infrastructure quality, financial discounts may affect commuters' perceptions of charger availability. Within congested networks, discounts may instill the belief that drivers need to shift to periods when campus chargers are unoccupied to secure an available charger and the discounts. In a follow-up financial intervention that primes perceptions of discount scarcity, we find that incentive-induced scarcity resulted in shifts to overnight charging sessions, highlighting that perceptions of scarcity alone shift charging behavior toward periods of lower utilization.

We evaluate what characteristics of drivers influence the timing of charging behavior as a response to the interventions. Greater commuting flexibility allows drivers to adjust their charging schedules in response to incentives, as evidenced by frequent commuters shifting to evening and overnight sessions during discount periods. Additionally, access to private home charging and low-cost overnight rates influences charging behavior, with drivers without

[2]This is consistent with literature that identifies charger scarcity as a central impediment to widespread EV adoption (Tal et al., 2014; Bornioli et al., 2023). Network congestion — i.e., when the number of EV drivers who wish to charge exceed available chargers — has been shown to influence driver behavior (Helmus et al., 2020). Some experiments have studied ways to reduce workplace charger scarcity by encouraging drivers to move their EV when done charging (Asensio et al., 2021; Bornioli et al., 2023).

home chargers or facing high charging prices at their usual location significantly shift to evening and overnight sessions in response to financial incentives.

In addition, we calculate the annual welfare effects per driver of each intervention. From the institution's perspective, annual welfare is the sum of avoided CO_2 emission damages, revenues from participation in local low-carbon fuel markets (California's Low Carbon Fuel Standard, or LCFS), and the cost of implementing the policy intervention. Using our experimental findings on the timing of campus charging sessions, informational treatment yields an annual net welfare benefit per driver of \$22.12 because charging shifts to midday when the grid has the lowest carbon intensity. In contrast, the first and second financial treatments reduce welfare by \$18 and \$4.97 (excluding the intervention costs) because charging shifts to early morning and evening hours, respectively, with higher grid carbon intensity. Finally, we highlight strong regressive patterns in the take-up of financial discounts for charging sessions, with benefits distributed unevenly across income groups.[3]

The literature on EV charging behavior has evolved along three dimensions: where and when drivers choose to charge their vehicles, why they make these choices, and how interventions can shape these decisions. Studies consistently show that the majority of charging occurs overnight (Helmus et al., 2020) at home (Lee et al., 2020) by EV drivers who tend to be wealthier and have higher rates of homeownership (Davis, 2019). Consequently, nearly all experimental work has sought to explain home charging behavior. With growing recognition that workplace charging will play a crucial role in fostering EV adoption (Dorsey et al., 2022) and in meeting the growing demand for charging (Tal et al., 2020), and as the profile of EV buyers shifts to adopters who are less wealthy and less likely to own a home, researchers must build analogous experimental literature around workplace charging.

We make three main contributions to the literature on workplace EV charging. First, we demonstrate how researchers can build an experimental basis for workplace EV research. We created an EV charging club for UCSD faculty, staff, and students whom we can enlist to study frontier research questions relevant to the workplace. The club provides financial and informational benefits to drivers in return for responding to periodic surveys that generate a rich set of data on driver, vehicle, charging, and commuting characteristics. We supplement this with charge session data, allowing us to analyze driver behavior in response to interventions.

Second, our work is the first to empirically examine the effect of interventions on the timing of workplace charging sessions, and complements the literature on temporal shifts

[3]This relates to literature on the distributional impacts of environmental policies, including gasoline taxes (Poterba, 1991; Bento et al., 2009), carbon taxes (Cronin et al., 2019), fuel economy standards (Davis & Knittel, 2019), building codes (Bruegge et al., 2019), utility rates (Borenstein, 2012; Borenstein et al., 2021), solar panel subsidies (Borenstein, 2017; Feger et al., 2022), and heat pump adoption (Davis, 2023).

in home charging (Bailey et al., 2023). We build on a rich literature of home and public charging experiments that suggests price-based and informational interventions can shape drivers' charging decisions. These include various pricing strategies (Motoaki & Shirk, 2017; Davis & Bradley, 2012; Langbroek et al., 2017; Kacperski et al., 2022), revenue opportunities (Lagomarsino et al., 2022), prizes and auctions (Fetene et al., 2017), financial penalties (Asensio et al., 2021), and financial discounts (Bailey et al., 2023). Informational interventions have also proven effective, including information on estimated cost savings (Nicolson et al., 2017), on charging sourced from renewable energy (Nienhueser & Qiu, 2016), and tailored at the point of charge (Asensio et al., 2021). While much research has focused on the technical potentials for automated load management (ALM) to optimize workplace EV networks (McClone et al., 2023), algorithmic solutions require that drivers first behave in preferred ways (i.e., plug-in at preferred times).

Third, our empirical findings can inform charging policy strategies intended to align charging with sustainability objectives. Institutions have implemented numerous practices and policies aimed at "managing" (i.e., improving the efficiency of) workplace EV networks — e.g., numerous fixed and volumetric pricing structures; digital queuing; time limits with pricing; valet services; day- and time-based restrictions; and public messaging systems (Sutton et al., 2022). Others include rewards, social charging apps, and policies on unplugging (Wolbertus & van den Hoed, 2017). However, research has found that these policies can inhibit workplace charging as much as they encourage it (Caperello et al., 2013; Bonges III & Lusk, 2016), e.g., by causing rather than alleviating congestion (Nicholas & Tal, 2015). As noted by Sutton et al. (2022), there is little evidentiary basis for how these policies affect driver charging decisions and the efficiency of the workplace network.

The rest of the paper proceeds as follows. Section II presents the experimental design and summarizes data. Section III provides the empirical methodology and experimental findings. Section IV discusses the welfare effects of the experiment. Section V concludes with policy implications.

II Experiment

The experimental setting assesses two interventions to promote daytime workplace charging: informational nudges and financial discounts. Specifically, we analyze whether information about the climate benefits of daytime charging and financial discounts for workplace charging influence *where* and *when* people charge. In addition, we examine the mechanisms, persistence, and interaction of these two treatments.

We conducted the field experiment at UCSD, which operates one of the world's largest

EV charging networks. We coordinate closely with campus administrators (UCSD's Transportation Services) responsible for campus charging policy and pricing as well as two leading charging vendors, ChargePoint and PowerFlex, who collect and share charge session data. To recruit research participants, we created a campus club for EV drivers — the "Triton Chargers"[4] — open to UCSD affiliates (students, staff, and faculty), in which drivers opt-in, consent to research, and receive discounts for charging on campus and opportunities to win raffle prizes (monthly $50 gift cards for being a member and larger quarterly gift cards for responding to surveys).[5] Appendix A.1 describes EV drivers at the UCSD campus. In return, members respond to recurring surveys that inquire about demographic information, their EV, commuting and driving, charging habits, motivations, and unique vendor identification numbers, allowing us to access individuals' campus charging activity and analyze potential behavioral shifts in response to interventions.

II.A Design of informational and financial interventions

The experiment consists of two interventions run in series — an informational treatment run over 18 days from October 4–23, followed by two phases of financial treatment run over 26 days from October 24 to November 19 (Figure I). Interventions were conducted within a single academic quarter to maintain consistency in campus population and schedules, and to ensure equal duration among the two financial treatments.

In the informational intervention, half of the study participants were randomly assigned to treatment and half to control. Treatment consists of an email, delivered three times (once per week), stating the climate benefits of daytime charging compared to nighttime charging. In each email, benefits are reported as avoided CO_2 emissions, equivalent unburned gasoline, and prevented global environmental damages. Appendix A.3 reports the email message and calculations for these quantities.

In the financial intervention, drivers were given discounts for all Level-2 charging and randomly placed into treatment arms that varied discount size.[6] The financial intervention consists of two phases.[7] During the first phase (October 24 to November 5; 13 days), roughly

[4]See https://deepdecarbon.ucsd.edu/triton-chargers.

[5]The Triton Chargers and associated experimental social science research at UCSD are part of a broader research testbed for distributed energy, called "DERConnect", that is open to outside researchers.

[6]The vast majority of UCSD chargers are Level-2. Participants report rarely using the small number of DC Fast chargers on campus and we exlude these from this study.

[7]One drawback to our design is that we do not have direct access to the prices charged by (or shown at) charging stations. Drivers pay the full price of their charging session and receive the discount incentive as a rebate at the end of the study period. If drivers disregard or forget our communications about incentives, they may be unaware of the incentive throughout the experiment. This may bias our estimates toward zero, but it represents potential real-world scenarios and follows previous research (Burkhardt et al., 2019)

one-third of participants receive a small discount ($\$.16/kWh$) and two-thirds receive a large discount ($\$.23/kWh$) — equivalent to 50% and 75% off the base campus rate of $\$.30/kWh$, respectively. We set discounts so that the effective small-discount rate of $\$.14/kWh$ corresponds to the cheapest overnight home charging rate of the local electric utility, San Diego Gas & Electric (SDG&E; $\$.145/kWh$ from midnight to 6 am during winter months) — thus negating the economic advantage of overnight home charging. While SDG&E's residential rates vary by time of day (Figure B3), campus rates and discounts apply equally to all hours of the day. The large-discount rate of $\$.07/kWh$ is equivalent to the locational marginal price of wholesale electricity, corresponding to the plausible lowest cost that drivers would pay for charging. Appendix A.4 summarizes the prompts for the financial discounts.

During the second phase (November 6–19; 13 days), half of the large discount group continues with the large discount, while the other half moves to the small discount. The second financial intervention thus has three treatment arms—LL (Large-Large), LS (Large-Small), and SS (Small-small) discounts—given to three distinct groups. In this phase, we test for the presence of habit formation when financial discounts are reduced. If the charging behavior of participants on reduced discounts (LS) closely mirrors those who continue to receive the large discount (LL), our results are consistent with habit formation. In contrast, if the charging behavior of participants on reduced discounts (LS) reverts to those receiving the small-small sequence of discounts (SS), our results indicate the absence of habit formation.

Appendix A.2 summarizes the full experimental schedule. All randomization is done via stratified block randomization based on drivers' commuting frequency (at least three times per week), preferred charging location (at or away from the home residence), and environmental motivations for choosing a charging location (high or low).

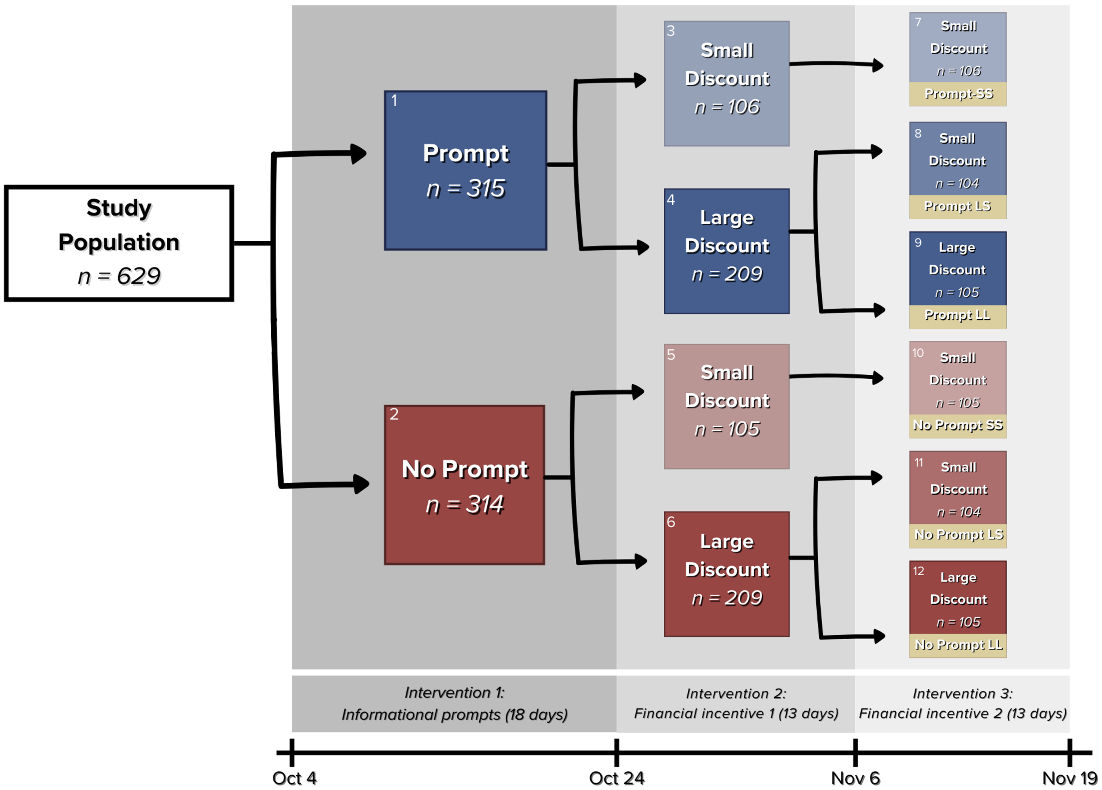


Figure I: Experimental design

Notes: This figure shows participant assignment to treatment and control groups over the three phases of our experiment: informational (Oct 4-23), first financial (Oct 24-Nov 5), and second financial (Nov 6-19). Figure A1 documents the full experimental schedule. Appendix A provides all details on the experimental design.

II.B Key datasets

1. *Charging network data.* The UCSD charging network includes 331 Level-2 chargers, including 250 ChargePoint and 72 PowerFlex chargers.[8] Campus rules permit 4 hours of charging at ChargePoint stations and 12 hours at PowerFlex. Stations record session data, including total session duration (marked by plug-in and plug-out times), charging duration, idle duration (time plugged in but not charging), and energy consumed.[9] They also record the unique (anonymized) ID of the driver who initiated the session, allowing us to link drivers to charging sessions. We exclude sessions that indicate an initiation error (i.e., that consume less than .5 kWh or last fewer than 5 minutes) or flout campus parking rules (i.e., exceed 16

[8]UCSD plans to install an additional 760 Level-2 and 35 DC Fast Chargers by the end of 2025.

[9]Some sessions in our dataset are fragmented, potentially due to software resets, driver actions such as unplugging and replugging, or data collection errors. We merge these session fragments and treat them as single charging events if the temporal gap between consecutive sessions is five minutes or less for a singular driver at a specific port.

hours; the maximum allowable duration is 12 hours, but we include a small subset lasting 12 to 16 hours). Appendix B.1 provides information on chargers and parking rules at UCSD.

2. *Driver data.* Upon enrolling in the Triton Chargers EV club, drivers provide information on their demographics (age, gender, income, and education), university affiliation, vehicle (year, make, model, type), living arrangement (rent or own, dwelling type), charging behaviors (access to charging alternatives, fraction of charging done by location), commuting behavior (commute frequency and distance, obtained via zip code),[10], and motivation for choosing campus charging locations (Table I, A–C). In addition, we periodically request odometer readings to track total driving before, during, and after interventions. Appendix A.5 and A.6 document the odometer and enrollment surveys.

3. *Other data.* In addition to campus charging, drivers can charge at home at rates set by the local utility (SDG&E) or at public destinations (e.g., malls, plazas) at rates set by the commercial operator. SDG&E public charging rates are tied to, but significantly higher than, the locational marginal price of electricity. Appendix B.2 summarizes SDG&E residential charging rates and wholesale electricity prices during the study period. To calculate the climate impacts of EV charging, which depends on the carbon intensity of electricity, we use emission factors published by the California Air Resources Board (Table B4).

II.C Descriptive statistics

Table I summarizes participants' demographics (Panel A), vehicle attributes (Panel B), and commuting and charging habits (Panel C), along with the outcome variables that reflect charging behavior (Panel D). Per self-reported survey responses, the average participant is 38 years old, has 17 years of education (equivalent to a Bachelor's degree), an annual income of $136 thousand, and makes 3.3 weekly commutes to campus. Panel A of Table C1 shows that participants are mostly staff (49%), faculty (21%), and undergraduate students (18%), who either own a single-family house owners (43%) or rent off-campus.[11] The average EV is 2.4 years old and has been driven 29,153 miles; 76% of EVs in our study are battery-electric. The mean daily driving mileage is 40 miles, and the mean one-way commute distance is 14 miles. 59% of participants report having a home charger. Drivers report paying, on average, $\$.18/kWh$.[12]

[10] We calculate the commute distance as the road network distance between the centroid of the driver's self-reported zip code and UCSD campus.

[11] 10% of our sample reports owning condos, bringing total homeownership to 54%, almost exactly that of the San Diego population. For our purposes, however, condo ownership and single-family house ownership are distinct because the latter have local control over decisions about installing home charging while condo owners may not.

[12] 190 participants (30% of the sample) report not knowing the price they typically pay to charge.

Per vendor session data, drivers initiated .89 weekly charging sessions on the UCSD campus during the experiment. The average session, charging, and idle durations were 312, 228, and 84 minutes, respectively. The average energy consumed was 19 kWh; the average cost was \$5.54. Participants did 30% of their charging on campus (on an energy basis).

Moreover, Panel B of Table C1 displays charging behavior patterns based on location, time of day, reasons for charging, and motivation to charge on campus. Drivers report that they charge mostly on campus (43%) or at home (39%) while also utilizing other locations such as charging plazas (5%) and destination charging (5%). Drivers report doing 39% of charging overnight and 19% during solar peak afternoon hours of 12-16. Drivers generally report price as the key factor in choosing a charging location. When on campus, where prices are the same everywhere, they report choosing charging locations nearest their office (39%) or where they think they are most likely to find an open charger (31%).

III Empirical results

III.A Methodology

To estimate the effect of the information and financial treatment on campus charging behavior, we run the following regression (1):

$$y_i = \beta Info_i + \delta Reward_{1i} + \eta(Info_i \cdot Reward_{1i}) + \gamma X_i + \alpha_j + \eta_t + \varepsilon_i, \quad (1)$$

where i indexes the driver; y_i refers to the charging outcome variable of interest; $Info_i$ and $Reward_{1i}$ are dummy variables equal to 1 if the individual received the informational prompts and large discount in the first financial treatment, and equal to 0 otherwise; the vector X_i represents a rich set of individual socio-demographic variables, vehicle characteristics, charging attributes, and motivation about charging;[13] η_t is a dummy variable for UCSD's "Clean Air Day" (Wednesday, October 4), a promotional event with 50% discounts on campus charging;[14] and α_j are vehicle fixed effects to control for time-invariant vehicle characteristics. The coefficients of interest β and δ measure the effect of the information and financial treatment on the outcome of interest. The coefficient η measures the interaction

[13]Control variables include age, gender, income, years of education, weekly days commuting to campus, vehicle age, vehicle type, odometer reading, an indicator for home charger, charging price, and being a charging club member. In addition, we include a dummy for the preferred charging location, usual charging time, motivations for charging location, and motivations when choosing where to charge on campus. As some respondents did not state their income and charging price, we use the average as a proxy for this variable.

[14]The Clean Air Day discounts only moderately increased the total charging activity of the Triton Chargers EV club (Figure A3), but it resulted in substitution to earlier charging (Figure A4).

Table I: Participant characteristics and charging behaviors

	Mean	Std. dev.	Min	Max	Obs.
A.Demographics					
Age	38.25	12.88	22	80	629
Share male (%)	0.53	0.50	0	1	629
Income ($ '000)	135.73	66.58	25	200	557
Years of education	17.18	3.09	11	21	629
Days on campus per week	3.26	1.75	0	6	629
B.Vehicle attributes					
Vehicle age (years)	2.38	2.59	0	22	629
Battery electric (%)	0.76	0.43	0	1	629
Odometer reading (miles)	29153.09	28770.26	28	205,069	422
C.Commuting and charging habits					
Daily mileage (miles)	39.95	40.83	0	491	318
Home charger (%)	0.59	0.49	0	1	629
Charging price ($ per kWh)	0.18	0.12	0	1	382
D.Outcome variables					
Share of charging on campus	30.70	34.60	0	100	313
Weekly charging sessions	0.89	1.21	0	9	629
Energy consumed (kWh)	18.72	12.32	1	67	401
Session costs ($)	5.35	3.53	0	18	401
Session duration (min)	312.33	170.62	23	792	401
Charging duration (min)	228.53	136.92	21	749	401
Idle duration (min)	83.79	102.51	0	614	401

Notes: This table reports descriptive statistics on driver demographics (Panel A), vehicle attributes (Panel B), commuting and charging habits (Panel C), and outcome variables of interest (Panel D) for experiment participants. Driver data (Panel A-C) are from the Triton Chargers EV club enrollment survey prior to the experiment; the outcome variables (Panel D), which characterize charging behavior, include all charging sessions between the first informational prompt (October 4) and the conclusion of the financial treatment (November 19). We report averages for age, income, and education, while our survey data asked respondents to select the appropriate bracket for each.

effect between information and financial treatment. For the second phase of the financial experiment, which estimates habit formation, we consider an analogous specification to that in equation (1), but we replace the $Reward_i$ dummy with an indicator variable $Reward_{2i}$ denoting 1 if an individual is in the large discount group in the second phase. In addition, we control for the first financial discount, $Reward_{1i}$, in the second phase. Standard errors are clustered at the individual-level.

We use the model specification in (1) to analyze total charging activity and the timing of charging. To measure changes in total charging, we analyze seven outcome variables: each driver's share of charging done on campus, the number of sessions initiated, energy consumed, session cost, session duration, charging duration, and idle duration (Panel D, Table I). A driver's share of charging on campus is the total energy consumed from campus charging divided by the expected energy consumed from total driving, which we estimate from data on the driver's daily vehicle miles driven obtained through recurring odometer readings and their vehicle's energy efficiency.[15]

To measure the effect of interventions on the timing of charging (i.e., the hour in which sessions are initiated), we analyze charging over five distinct periods: overnight (21:00–4:59), characterized by low network utilization; early morning (5:00–6:59), which sees the earliest morning commuters and has low utilization; morning (7:00–9:59), characterized by the arrival of most regular commuters and a rapid surge, to near maximal levels of network utilization; midday (10:00–15:59), characterized by relatively constant high utilization and maximal solar generation; and evening (16:00–20:59), characterized by departing commuters, arrival of nighttime workers, and rapidly waning solar generation. Californians are incentivized through time-of-use pricing to avoid energy use during especially the evening period.

1. *Balance.* Table C2 provides balance tests to assess the quality of our three randomizations. Specifically, we compare mean values for demographics, vehicle attributes, and commuting and charging habits across treated and control groups of the informational, the first and second financial interventions. Using a one-way ANOVA test, the table shows that the randomization achieved balance across most observed covariates.

III.B Main findings

This section reports empirical results on total charging behavior and the timing of charging during the informational and financial treatments.

[15]We assume participants with plug-in hybrids drive on electricity only for a subset of total miles, with longer electric-only ranges corresponding to lower reliance on gasoline (Isenstadt et al., 2022).

1. *Effect on total charging behavior* Figure II shows daily total charging activity for six measures of campus charging: the number of charging sessions (Panel A); total energy consumed, in kWh (Panel B); (pre-rebate) session cost, in U.S. dollars[16] (Panel C); session duration, in hours (Panel D); charging duration (Panel E); and idle duration (Panel F) across the two interventions for the treatment and control groups. The informational and first financial intervention each consist of a single treatment and control group; the second financial intervention has three treatment arms consisting of large-large (LL), large-small (LS), and small-small (SS) combinations of discounts during the first and second financial discount, respectively. Across all measures, the raw session data show no striking difference between these groups. Although there is a slight increase in total energy consumed and charging duration among treated individuals on day 3 of the informational intervention, we do not observe any evident shifts in individuals' total charging behavior.

Table II provides the regression estimates for the informational treatment (Panel A), two financial treatments (Panel B–C), and interaction effects between information and the first large discount (Panel D). Neither the informational nor the first financial treatment significantly affected any of the seven measures of total charging behavior. These results suggest that these incentives neither encouraged additional drivers to charge on campus (i.e., switch from off-campus to campus charging) nor motivated existing drivers to charge more frequently. First, this suggests that total workplace charging behavior is not impacted by the environmental appeal of daytime charging, consistent with results from a similar, smaller trial experiment in June 2023 (Appendix A.8).[17] Second, financial discounts for workplace charging do not change individuals' total charging activity.[18] This is consistent with the lack of a significant increase in charging sessions and energy on the Clean Air Day (Appendix A.7).[19] These results hold for both charger vendors (Table D2).

In contrast, the second financial discount (in which half of the large discount group continues with the large discount) results in an increase of .434 (25%) in the number of campus charging sessions. In addition, the second financial discount induces longer charging and idle

[16] We use the term "session cost" to refer to the cost of a charging session before any charging discounts are applied.

[17] One possible explanation for the non-existing treatment effect is information spillover, i.e. that information about climate benefits diffused from treated to non-treated participants. However, spillover effects are unlikely to explain our results since there is no significant increase in workplace charging immediately after the experiment.

[18] Related to the literature on rebound effects in the context of fuel efficiency (Chan & Gillingham, 2015; Gillingham et al., 2020), the discounted charging could plausibly have led to an increase in driving. However, we find no evidence that drivers increased their mileage, charging frequency, or campus energy consumption in response to the financial incentive.

[19] During the first three weeks of October, Figure A3 indicates a non-significant 10% increase in total energy consumed on Clean Air Day compared to other Wednesdays.

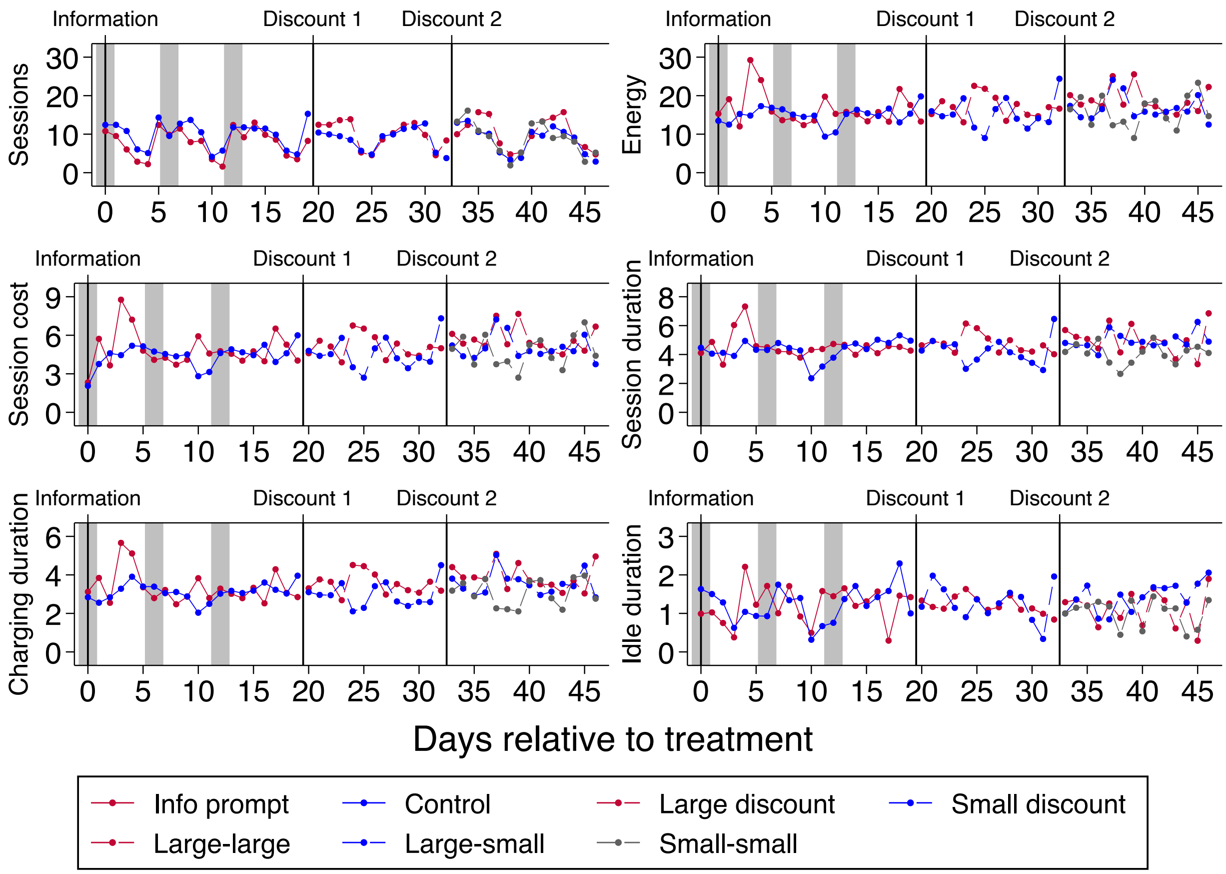


Figure II: Total charging behavior by day

Notes: This figure shows the total charging activity by treatment and control group. Shown are the number of charging sessions (Panel A); total energy consumed, in kWh (Panel B); session cost, in U.S. dollars (Panel C); session duration, in hours (Panel D); charging duration, in hours (Panel E); and idle duration, in hours (Panel F). Session duration is the sum of charging and idle duration. Day 0 denotes the first day of the informational treatment (October 4). Dashed vertical lines denote the start of the informational (Day 0), first financial (Day 18), and second financial treatment (Day 33). Gray vertical bars denote days on which information prompts were sent.

durations, which suggests that the larger discounts are associated with longer sessions (Table D1).[20] This may imply that drivers either adapt to the extended financial incentives (i.e., require time to establish new charging habits) or that providing discounts to fewer drivers diminishes perceived scarcity of available chargers and to secure the associated discounts.

Although we do not observe any significant changes in total campus charging, our interventions prompted a redistribution among a few commuter groups. Specifically, we noted a shift in the number of charging sessions from high-utilization garages to medium-utilization garages during the informational treatment (Table D3), and a slight increase in campus charging by commuters who experience low glitch rates during the second financial discount (Table D5). This may suggest that informational and financial treatment result in larger campus charging responses for workplace charging facilities characterized by lower congestion and greater reliability. In addition, we observe a slight substitution in total charging behavior from infrequent to frequent commuters (Table D7), indicating that interventions may have a more pronounced effect on commuters with greater flexibility regarding whether to charge on a given trip to campus.

2. *Effect on the timing of charging behavior* Next, we transition to temporal shifts in charging behavior. Figure III shows the average number of charging sessions and energy consumed per driver, by hour of the day, over the course of each intervention − the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C).[21] To calculate total energy delivered, we assume that energy is dispensed to the EV uniformly while actively charging. During each intervention, most charging sessions are initiated during 7–9 am, with a second smaller peak around 12 pm. Most energy is delivered over 9 am – 3 pm once most EVs are plugged in.

Information led to a substantial decrease in charging sessions initiated between 5–7 am, but a slight increase in initiated sessions between 7–10 am (Panel A). In addition, we observe a reduction in initiated sessions between 3–9 pm. Conversely, the first financial intervention shifts charging to 5–7 am (Panel B). Although the effect on these early morning sessions disappears during the second financial discount, we observe a considerable increase in initiated sessions between 5–9 pm. Consequently, environmental prompts seem to effectively contribute to postponed scheduling of morning sessions and fewer late afternoon and evening

[20] Although the informational and first financial treatment exhibit no significant effect on the average energy, session cost, or duration of charging sessions, we observe two non-significant shifts: a decrease in charging duration due to informational intervention and an increase in the charging duration due to the financial discount. One plausible explanation is that discounts induce drivers to plug in earlier in the morning, leading to longer stays on campus and longer duration sessions. In contrast, the informational treatment causes drivers to arrive later in the morning, resulting in shorter sessions.

[21] Analogous results for the other measures of total charging, e.g. cost and duration, are given in Figure C9.

Table II: Effect on total charging behavior

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge time	(7) Idle time
A. Informational prompt	.501	-.002	-1.471	-.589	-47.084	-18.950	-28.159
	(3.673)	(.269)	(5.365)	(1.485)	(101.501)	(69.166)	(48.349)
Mean Dep. Var.	30.37	2.47	42.67	11.89	784.07	547.62	236.43
B. Financial incentive 1	-.170	-.040	5.349	1.546	46.346	53.400	-7.051
	(4.029)	(.199)	(3.917)	(1.133)	(68.710)	(49.377)	(29.872)
Mean Dep. Var.	34.67	1.71	30.84	8.91	549.03	390.56	158.48
C. Financial incentive 2	1.824	.313	5.127	1.537	89.069	62.649	26.454
	(4.821)	(.251)	(5.551)	(1.616)	(91.692)	(67.101)	(39.365)
Mean Dep. Var.	31.89	1.73	31.6	9.17	560.06	391.2	168.85
D. Information x large discount	-2.195	-.070	.601	.119	-94.626	-34.872	-59.771
	(3.732)	(.461)	(8.775)	(2.464)	(166.376)	(112.816)	(82.161)
Observation	350	629	629	629	629	629	629

Notes: This table presents the regression estimates of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as interaction effects (Panel D). The outcome variables indicate the share of campus charging (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration, in minutes (column 6); and idle duration, in minutes (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. The number of observations is reported in the last row. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

sessions—both of which lead charging to better align with solar energy generation. Financial incentives induce a shift to earlier morning and overnight charging, driven by greater evening arrivals on campus.

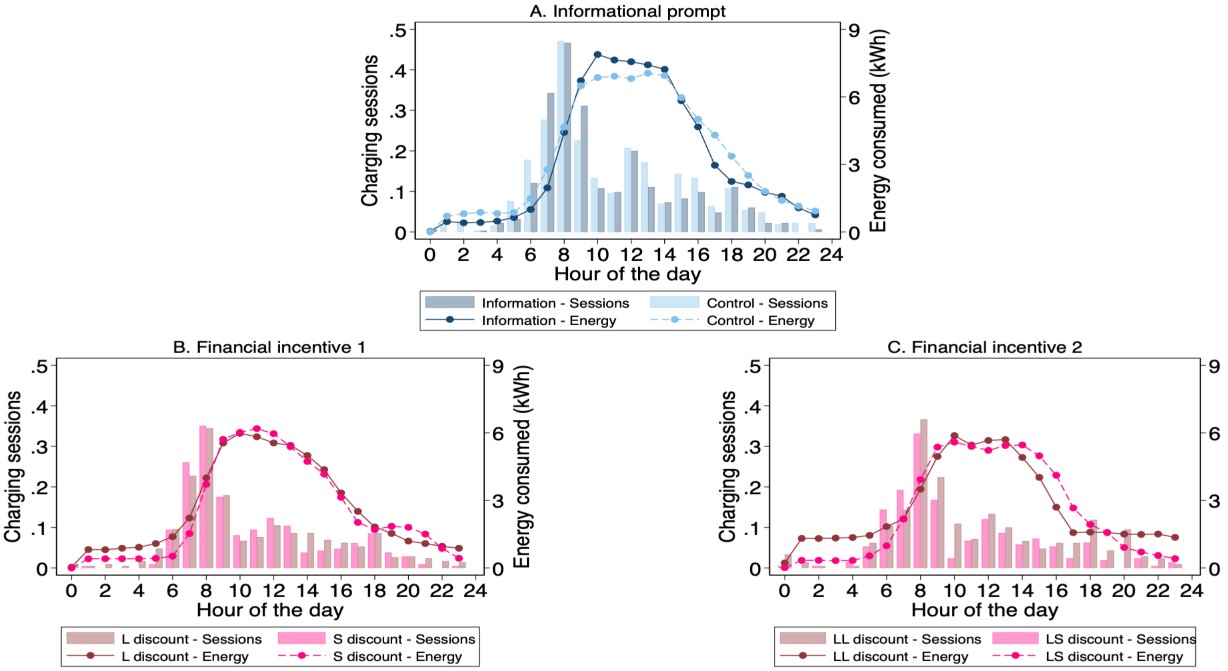


Figure III: Number of charging sessions and energy consumed by hour of the day

Notes: The figure displays the average number of charging sessions and energy consumed per driver, by hour of the day, over the course of each intervention – the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C). Bars indicate charging sessions; lines denote energy consumed. To calculate total energy delivered, we assume that energy is dispensed to the EV uniformly while actively charging.

Table III presents the regression estimates of the daily temporal distribution of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as the interaction between the information and first financial incentive (Panel D). The informational treatment resulted in a significant decrease of .133 (67%) in early morning (5–7), which was compensated by an (insignificant) increase in charging during the morning (7–10). Given an average of .89 weekly campus charging sessions per driver, around 15.4% of sessions were shifted away from early morning. This indicates a pronounced intertemporal substitution effect, wherein the environmental prompts induced a shift from early morning toward daytime charging when solar energy generation is more abundant.

Conversely, the first financial discount for workplace charging yielded a significant increase of .072 (103%) in overnight (21–5) and .073 (61%) in early morning sessions and an (insignificant) decrease in charging over the rest of the day. This pattern suggests an intertemporal substitution in the opposite direction — outside of the solar midday period. This is consistent with charging behavior during the Clean Air Day, which saw drivers initiate earlier charging sessions.[22]

Finally, the second financial discount for campus charging led to a significant increase of .226 (35%) in midday (10–16) and .229 (88%) in evening sessions (16–21), but offset the influence of charging sessions initiated overnight and early morning. Drivers who received large discounts were not more likely to charge overnight or during early morning compared to those who were switched to small discounts in the second phase. Put differently, the effect on overnight and early morning charging during the first large discount had no lasting effect, which reflects an absence of habit formation after the first financial treatment.[23] The shift to midday sessions could reflect that drivers' require time to internalize the discounts before adjusting their charging behavior. The shift to evening sessions also causes longer session and idle duration (Table D1). In addition to the intra-day shifts of charging sessions, we provide evidence that commuters slightly increase their total energy consumed on weekends during the financial treatments (Table D10), suggesting potential intra-week substitution of charging sessions.

III.C Mechanisms

To assess the mechanisms behind the temporal shifts in campus charging, we empirically test three factors that may explain the temporal shifts in charging sessions: the "quality" (i.e., reliability and availability) of campus charging infrastructure (Section 1.), the effect of experimental incentives on perceptions of charger scarcity within the campus charging network (Section 2.), and the characteristics of drivers, in particular their commuting flexibility and whether they have access to home charging (Section 3.).

We focus on these three mechanisms for (at least) three reasons: First, drivers have reported difficulty finding an available and reliable charger on campus in the enrolment survey, aligning with existing literature highlighting these as common shortcomings in public charging infrastructure.[24] Second, scarcity concerns emerged as a potential explanation for the

[22] On Clean Air Day, there was a shift in charging sessions from midday to morning (Figure A4, Panel B), indicating that the 50% discount on charging rates may motivate drivers to arrive earlier to work to secure an open charger.

[23] One potential explanation is that our study occurred over a relatively short timeframe. Given that drivers charge roughly once per week, our estimated treatment effects should be interpreted as short-term effects and drivers may require a longer horizon to form charging habits. Alternatively, as the pool of drivers receiving the large discount was halved in the second financial treatment, drivers may learn over time that such early morning arrivals are not necessary to secure a charger.

[24] Charger unreliability is a known impediment to EV adoption and charging. For example, Rempel et al. (2022) report that only 73% of DC fast charger ports sampled in the Greater Bay Area in 2022 were operational, far below the 95–98% range claimed by EV service providers.

Table III: Effect on the timing of charging

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A. Informational prompt	-.048	-.124*	.202	-.049	.017
	(.044)	(.072)	(.176)	(.137)	(.083)
Mean Dep. Var.	.09	.2	1.05	.75	.37
B. Financial incentive 1	.061**	.084*	-.076	-.043	-.046
	(.030)	(.049)	(.130)	(.092)	(.062)
Mean Dep. Var.	.07	.13	.76	.49	.26
C. Financial incentive 2	.040	-.061	-.002	.194*	.205**
	(.062)	(.082)	(.140)	(.121)	(.093)
Mean Dep. Var.	.07	.19	.71	.63	.26
D. Information x large discount	-.045	-.146	.106	.011	.003
	(.077)	(.115)	(.313)	(.215)	(.144)
Observation	629	629	629	629	629

Notes: This table presents the regression estimates for the time of day in which sessions are initiated for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as the interaction effect between information and the first financial treatment (Panel D). The outcome variables indicate the number of initiated charging sessions during overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, as well as vehicle-fixed effects. The mean outcome variable is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

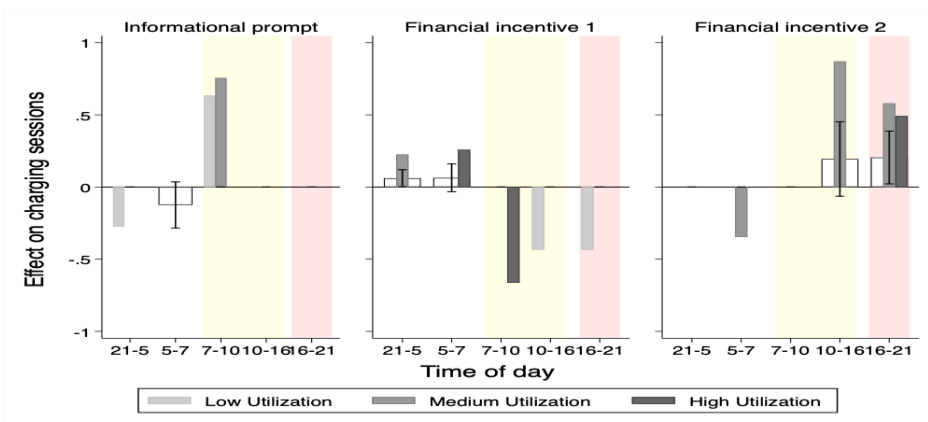
temporal shifts in the first financial experiment, with greater early morning charging indicating intensified competition for chargers due to limited availability. Third, analyzing driver characteristics is critical for identifying which socio-demographic groups respond most to our interventions, thereby targeting interventions toward the most responsive socio-demographic groups. Understanding the mechanisms can help institutions and policymakers predict temporal shifts in charging behavior depending on the characteristics of their charging networks, incentives, and commuters.

1. *Quality of charging infrastructure.* We test two charging network attributes that plausibly affect drivers' charging decisions. The first is high network utilization, defined as the fraction of chargers used during a given hour, which could discourage drivers from charging on campus. As Figure V illustrates, by 9 am the two largest campus zones (West Campus and East Campus) typically experience 80–90% weekday utilization, while all other zones experience over 50% utilization.[25] Periods of high utilization largely align with periods of low grid carbon intensity.

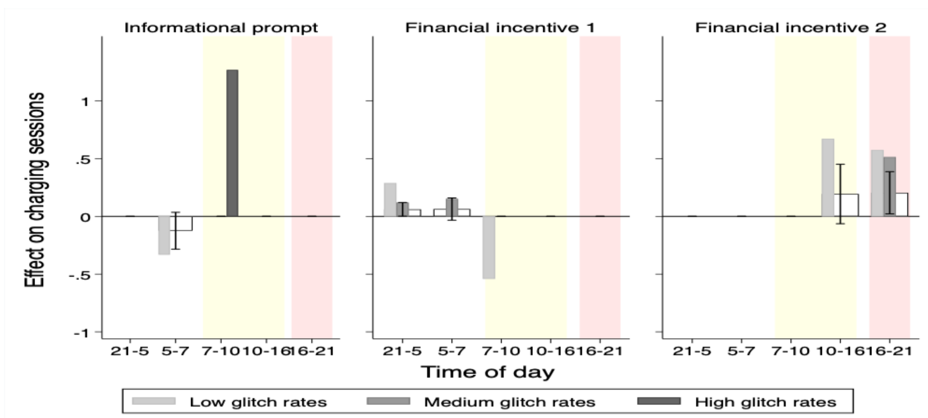
To empirically estimate whether network utilization is a mediating factor in our estimated temporal shifts in campus charging during the interventions, we run separate regressions for drivers who do their modal charging at low, medium, and high utilization garages — defined as garages with $\leq 60\%$, $60-75\%$, and $\geq 75\%$ utilization, respectively, during the morning commute period (7 – 12 pm). We observe that the informational and financial interventions affect drivers who typically charge in low- and high-utilization garages differently (Figure IVa). In response to informational prompts, the drivers who shift from overnight to morning charging are exclusively those who typically charge in low-utilization garages. This suggests that drivers' responsiveness to non-financial informational prompts and willingness to change behavior is higher when there is a perceived lack of charger scarcity.

In contrast, financial discounts predominantly affect drivers who use medium- and high-utilization garages. These drivers shift charging to periods with lower network utilization: during the first financial incentive, they shift toward overnight and early morning charging, whereas during the second financial incentive, they shift toward evening charging. These shifts may reflect an expectation that large discounts on charging will intensify competition for chargers that are already highly utilized during peak periods, and, consequently, that drivers in garages with high utilization rates may need to shift charging to periods with lower utilization to guarantee they receive a charge. Consistent with drivers' concerns about

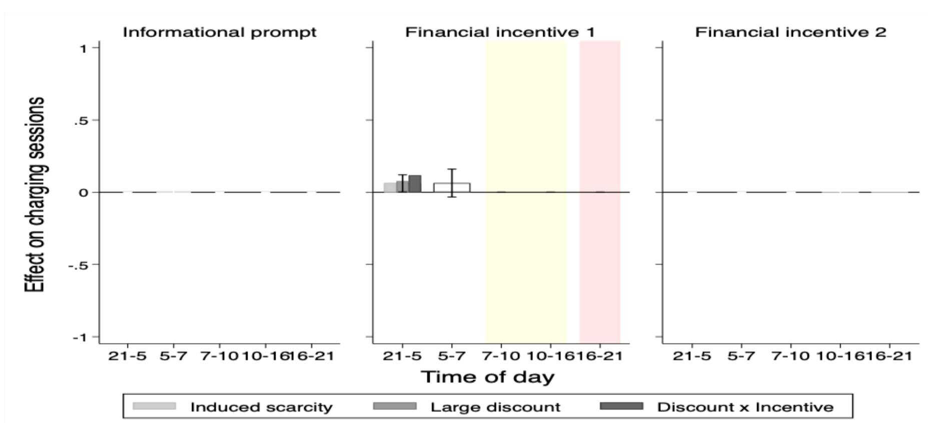
[25] We calculate "effective" network utilization, which excludes chargers that are temporarily non-operational or out-of-service (Appendix C.2). These estimates represent a lower bound because we do not detect when stalls are occupied by non-charging vehicles (e.g., non-EVs parked in EV charging spots or EVs exploiting favorable parking opportunities without charging). Appendix C.3 summarizes network utilization at UCSD.



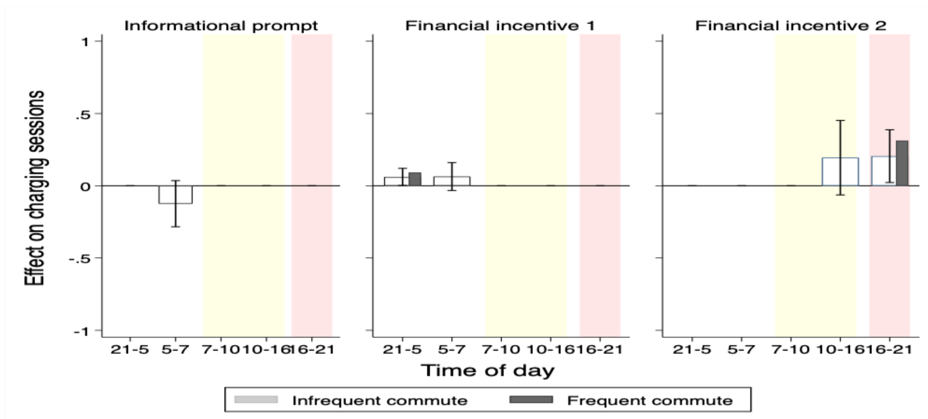
(a) Network utilization



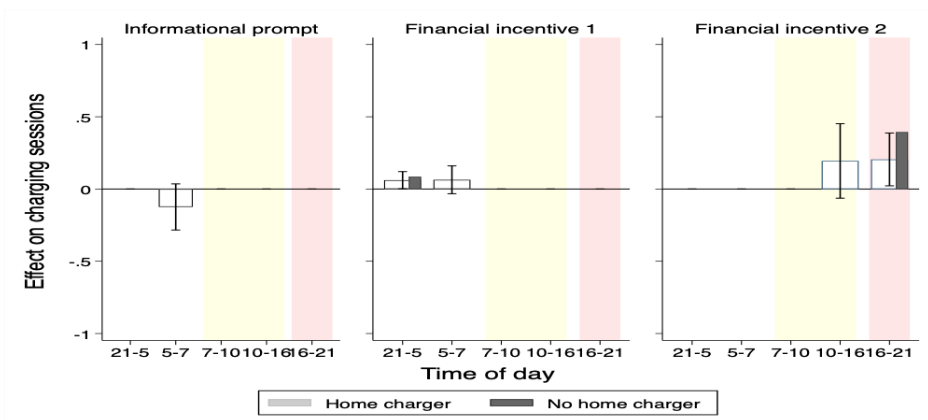
(b) Charger unreliability



(c) Incentive-induced scarcity



(d) Commute frequency



(e) Access to home charger

Figure IV: Effect on the timing of charging by mechanisms

Notes: This figure displays the significant regression estimates (hollow bar) for the time of day in which sessions are initiated across the informational (left), first financial (middle), and second financial treatment (right). We show significant treatment effects (solid bars) on the timing of charging sessions for five mechanisms: Network utilization (Panel a), session glitch rate (Panel b), incentive-induced scarcity (Panel c), commute frequency (Panel d), and access to home charging (Panel e). Morning and midday periods are associated with low grid carbon intensity (7 - 16; depicted in yellow), whereas evening periods typically exhibit higher carbon intensity (16 - 21; depicted in red). Section D.3 provides the corresponding regression results on the timing of charging behavior. We set statistically insignificant estimates to 0. 95%-confidence intervals are indicated through whiskers and reflect robust standard errors.

charger scarcity, these temporal shifts induced by the financial discount occurred primarily in campus zones with high network utilization (Table D12).

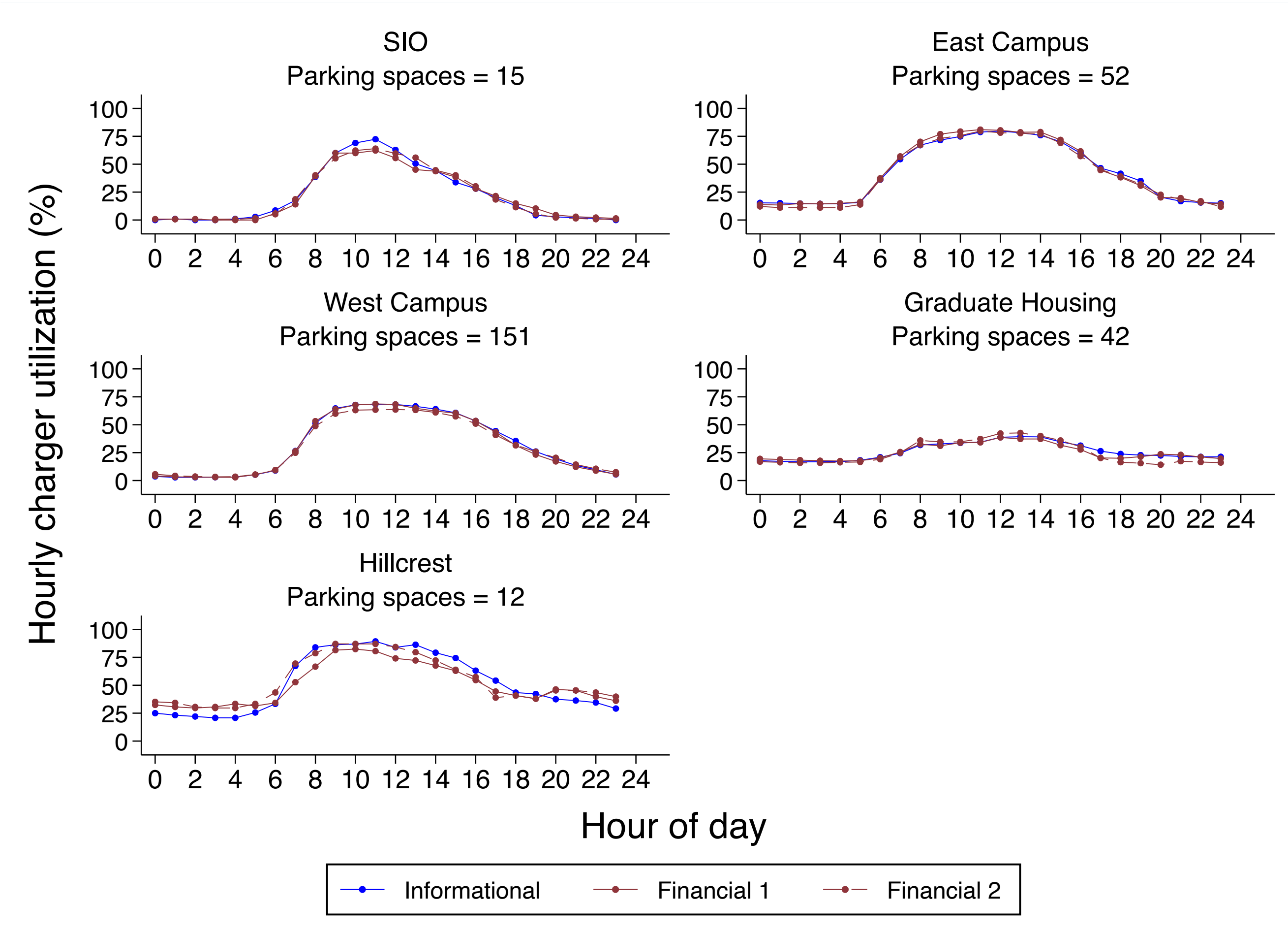


Figure V: Network utilization by time of day and campus zone

Notes: This figure shows the effective hourly utilization of chargers for the five campus zones over the experiment period (October 4 - November 19). We define the effective hourly charger utilization as the percentage of chargers used in a given hour relative to all chargers used during the experiment period. We exclude chargers that are non-operational and out-of-service. Figure B2 shows the five distinct parking zones on the UCSD campus.

The second network attribute that could discourage drivers from charging on campus is the perceived unreliability of chargers. We measure this unreliability of chargers as the percentage of charging sessions that "glitch" (i.e., that fail to deliver a meaningful energy), which varies between 15 to 20% daily for PowerFlex and ChargePoint chargers on campus (Figure C7). Of all attempts to charge during our study, only 86% yielded meaningful energy (> 0.5 kWh).[26] Moreover, drivers who unsuccessfully plug in on their initial attempt are less

[26]Charging attempts may fail due to user error, physical charger damage, software bugs, or device or app

likely to receive a charge during successive attempts (Figure C8).

Because these failed attempts occur more frequently in particular garages, we assess whether charger unreliability was a cause of the temporal shifts in campus charging by comparing drivers that experience a low ($\leq 10\%$), medium ($10 - 20\%$), and a high rate of failed sessions ($\geq 20\%$), or "glitch rate", at their modal garage. Consistent with the hypothesis that drivers are more willing to shift their charging behavior when chargers are reliable, drivers who charge at low-glitch-rate garages drive most temporal shifts in charging during all interventions (Figure IVb). During the informational intervention, these drivers shift charging away from early morning; during the first financial intervention, they shift from morning to overnight; and during the second financial intervention, they shift to midday and evening.[27] Consistent with the charger unreliability mechanism, we find that the temporal shifts to evening and overnight charging during the financial interventions mainly stem from the ChargePoint stations, which have significantly lower glitch rates (Table D14).

2. *Experimental incentive structure.* In addition to the quality of network infrastructure, financial discounts themselves could in turn increase drivers' perceptions of scarcity if drivers believe lower charging rates induce greater campus-wide charging. An "induced" expectation of additional network use could decrease drivers' inclination to charge on campus or deviate from existing charging patterns in response to discounts.

To test whether incentive-induced scarcity was a cause of temporal shifts in campus charging during the interventions, we conduct a follow-up financial intervention that is similar to the first financial discount but that additionally primes drivers' beliefs about the number of EV drivers who receive the discount (Appendix A.9). In this follow-up intervention, the scarcity treatment group received a notification implying that the entire Triton Chargers EV club would get the discount, while the control group received a similar notification implying that only one-third of the club would receive the discount.

Incentive-induced expectations of scarcity resulted in shifts to overnight charging sessions equivalent in magnitude to those of the financial discount intervention (Table D15), suggesting that drivers' expectations of additional incentive-induced campus charging have an impact nearly equivalent to the incentives themselves.[28] The interaction between scarcity and discounts led to an even larger increase in overnight charging sessions, underscoring how

connectivity.

[27] We observe a temporal shift caused by drivers that experience higher glitch rates in one case: a shift to morning charging in the informational intervention. One possible explanation is that these high-glitch-rate garages also have lower utilization, indicating that availability eclipses unreliability.

[28] Notably, the responses to large financial discounts closely mirror our main findings presented in Table III. A potential explanation for the absence of a shift towards early morning charging could be drivers' expectation that heavily discounted charging rates led to increased competition for chargers in the morning as in the first financial experiment, prompting them to seek charging during low-utilization periods.

scarcity concerns combined with financial incentives can prompt significant temporal shifts to periods of low utilization. Thus, the incentive-induced perception of scarcity can explain our observed shifts toward overnight charging when the network is less congested.

3. *Driver characteristics.* Drivers who have greater flexibility in their decisions about when to commute to campus and charge may be better able to adapt their commuting and charging schedules in response to nudges and discounts (Kacperski et al., 2022). To test whether greater commuting flexibility influences charging behavior, we compare the temporal shifts of commuters with different commute frequency. Given our context as a workplace charging network, we identify drivers who commute frequently ($\geq$ 3 times per week) as possessing higher flexibility, as they can select from a variety of days for charging. Frequent commuters are solely responsible for the shift to evening and overnight sessions during the first and second discount (Figure IVd), suggesting that commuter groups with greater flexibility are more likely to adjust their charging schedule.

An additional driver characteristic that could deter the use of workplace charging is access to private home charging and low-cost overnight charging rates, which render home charging a more convenient option (Jabeen et al., 2013). Consistent with this mechanism, we find that providing financial discounts induces large shifts to evening and overnight charging sessions from drivers without a home charger (Figure IVe) or those who report paying high modal prices for charging at their usual location (Table D18). These results imply that the convenience of residential charging for treated drivers plays a key role in how financial incentives shift the timing of charging sessions.

IV Welfare implications

IV.A Welfare effects

We estimate annual net welfare effects per driver, from the institution's perspective, from intertemporal behavioral shifts observed in each of the information, first financial, and second financial treatments.[29] We focus on the welfare effects of intertemporal substitution, leaving aside the effects of shifting charging to campus that require further assumptions to calculate off-campus charging. In our calculations, we consider two categories of social benefits: First are avoided damages of CO_2 emissions, denoted $\triangle CO_2$, equal to the product of the change in CO_2 emissions corresponding to temporal shifts in charging and the social cost of carbon (equation 3). Second are revenues earned through the Low Carbon Fuel Standard (LCFS)

[29]From the global perspective, intervention implementation costs are a transfer from the institution to drivers receiving the discounts and hence would not a part of global welfare effects.

program, denoted $\triangle LCFS$, equal to the product of the change in electricity consumption by hour and the carbon intensity of electricity at that hour (equation 4). We contrast these benefits to the cost of implementing the intervention, $\triangle Costs$, calculated as the product of the per-kWh discount size and energy consumed for all qualifying charging sessions (equation 5).

Focusing on marginal changes induced by the experiment, the net welfare $\triangle W$ is the sum of avoided CO_2 emission damages, LCFS revenues, and intervention implementation costs per driver annually:

$$\triangle W = \underbrace{\triangle CO_2}_{Global\ pollutant} + \underbrace{\triangle LCFS}_{Local\ benefit} - \underbrace{\triangle Costs}_{Local\ costs} \tag{2}$$

Table IV summarizes the annual welfare effects for each intervention, per equation (2). We convert average treatment effects over the experiment (18 days of informational prompts; 13 days of each discount) to annual effects. For the informational treatment, the net per-driver welfare effect is \$22.12 because information leads to less early morning and greater morning charging. This comes from a \$12.51 reduction in carbon emissions and \$9.61 earned LCFS revenue from shifting charging sessions to hours with lower grid intensity. In contrast, the net welfare effect of the first financial treatment equals $-$\$346.38 per driver, resulting from an increase in carbon emissions ($-$\$10.23) and LCFS revenue ($-$\$7.67) by shifting to early morning charging hours with higher grid intensity. In addition, the financial discounts paid to the drivers correspond to an average cost of $-$\$328.48. The net welfare effect of the second financial treatment equals $-$\$373.64 per driver, which results from an increase in CO_2 emissions ($-$\$5.8) and LCFS revenue (\$.83) by shifting to late evening charging hours with higher grid intensity. In addition, the financial discounts paid to the drivers correspond to an average cost of $-$\$368.66.

From the perspective of UCSD, when considering the effect on all Triton Charger EV club members and treating intervention costs as transfers (i.e., omitting intervention costs), the informational prompts increased welfare by \$13,913 due to shifts in the timing of charging, while the first and second financial discounts decreased welfare by -\$11,259 and -\$3,126, respectively. If scaled to all EV owners in California (currently 1.29 million vehicles), the informational treatment would avoid CO_2 emission damages equal to \$16.1 million, —\$13.2 million from the first discount, and —\$7.5 million from the second.

Table IV: Welfare effect decomposition

	Intervention ($)		
	Information	Discount 1	Discount 2
Avoided CO_2 damages ($\triangle CO_2$)	12.51	−10.23	−5.8
LCFS revenues ($\triangle LCFS$)	9.61	−7.67	.83
Intervention costs ($\triangle Costs$)		−328.48	−368.66
Welfare effects ($\triangle W$)	**22.12**	**-346.38**	**-373.64**

Notes: This table reports the annual welfare effects per driver, from the perspective of the institution, from changes in the timing of charging sessions, per equation (2). Welfare effects are reported for the informational (column 1), first financial (column 2), and second financial treatment (column 3).

Avoided CO_2 emission damages. To estimate the monetary implications of the carbon emission changes, we compute how treatment affects commuters' charging-induced CO_2 emissions. Equation (3) displays the hourly charging-related carbon emission changes that arise through the information and financial treatment for each hour h of the day:

$$\triangle CO_2 = \sum_{h=1}^{24} (\underbrace{\beta_h^{kWh} \cdot CI_h}_{Information} + \underbrace{\delta_{1h}^{kWh} \cdot CI_h}_{Discount\ 1} + \underbrace{\delta_{2h}^{kWh} \cdot CI_h}_{Discount\ 2}) \cdot SCC. \tag{3}$$

The coefficients β_h, δ_{1h}, and δ_{2h} indicate how the informational, first financial, and second financial treatment affect the total energy consumption (kWh) during each hour of the day (Figure VI). The coefficients refer to the effect on average energy consumption between the plug-in time and plug-out time. CI_h refers to the hourly carbon intensity (gCO_2/MJ) per the California Air Resources Board Low Carbon Fuel Standard (Figure B4).[30] Multiplying this by the social cost of carbon (SCC) of 210 $\frac{\$}{tCO_2}$ following the estimates from the Environmental Protection Agency (2022) yields the total cost of carbon emissions.

The left Panel of Figure VI shows the changes in hourly carbon emissions (in kilograms of CO_2) due to intertemporal shifts in charging during the informational and two financial interventions. The informational prompts cause a decrease in carbon emissions, particularly from 5–7 am when drivers shift charging away from this period, resulting in a total reduction of 1 to 3 kilograms of CO_2 per driver over the course of the intervention. In contrast, the first financial intervention is associated with an increase in carbon emissions between 5–7 am of 0.5–2 kilograms of CO_2 due to greater early morning charges. The second financial discount results in an increase of carbon emissions of up to 2 kilograms from charging between 4–8

[30] To transform the carbon intensity factor from gCO_2/MJ into tCO_2/kWh, we multiply CI_h by 3.6 $MJ/kWh \cdot 10^{-6} t/g$.

pm and a slight increase overnight. Aggregating the carbon emission changes over the day, the informational treatment yields annual net benefit of \$12.51 per driver, while the first and second financial treatment results in net losses of \$10.23 and \$5.8.[31]

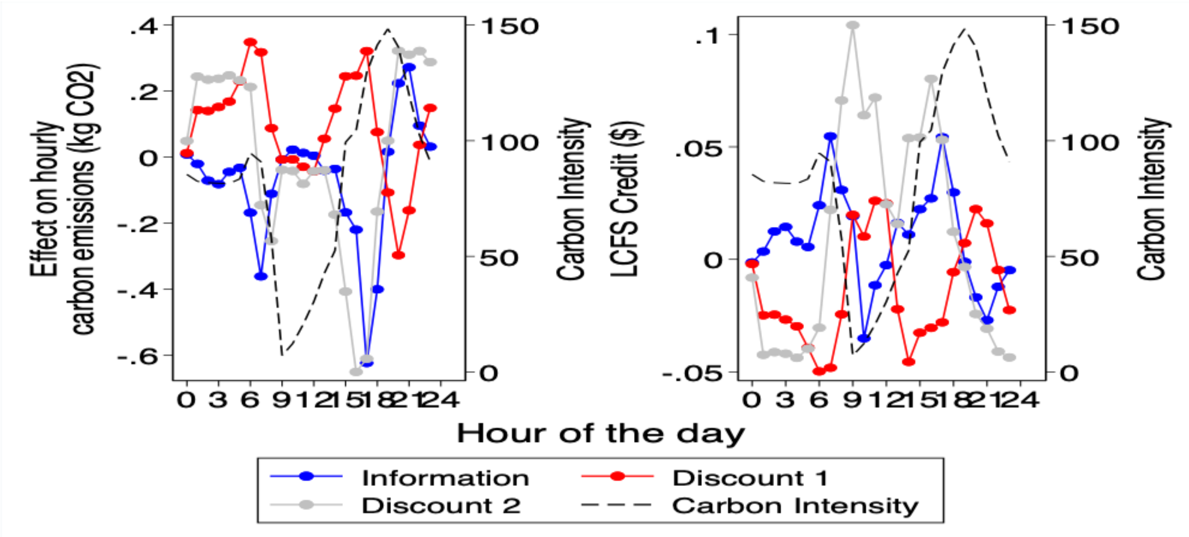


Figure VI: Effect on hourly CO_2 emissions and LCFS revenue

Notes: The left figure displays the changes in hourly CO2 emission per equation (3) due to the informational, first financial, and second financial treatment. The right figure displays the change in LCFS revenues per equation (4) due to the informational, first financial, and second financial treatment. The black dashed line denotes the quarterly carbon intensity from the California Air Resources Board in 2022.

LCFS revenues. The LCFS is designed to decrease the carbon intensity of California's transportation fuel pool and provide an increasing range of low-carbon and renewable alternatives, which reduce petroleum dependency and achieve air quality benefits.[32] We calculate the hourly LCFS revenue from changes in the timing of charging in equation (4) as:

$$\triangle LCFS \;=\; \sum_{h=1}^{24}(CI_{standard} - CI_h/3.4)\,\cdot\,(\beta_h^{kWh} + \delta_{1h}^{kWh} + \delta_{2h}^{kWh})\,\cdot\,\bar{P}\,\cdot\,3.4. \tag{4}$$

where $CI_{standard} = 89.5\ gCO_2/MJ$ is the typical carbon intensity from gasoline-powered cars, and $\bar{P} = 64.51\ \$/t$ is the LCFS credit price per ton. $CI_{standard}$ is multiplied by 3.4, which is the Energy Economy Ratio showing the fuel-feedstock combination displacing gasoline with a light-/medium-duty EV.

The right Panel of Figure VI illustrates the effect of each treatment on LCFS revenues.

[31] As the shifts to earlier arrivals may partly be due to the congested network, financial discounts in low utilization networks may not result in an increase of CO_2 emissions.

[32] The LCFS Credit Transfer Activity Reports can be found at https://ww2.arb.ca.gov/resources/documents/weekly-lcfs-credit-transfer-activity-reports.

Aggregated over the course of the day, the informational treatment increases the LCFS credit by \$9.46 per driver. In contrast, the financial treatment leads to a reduction of $-\$7.67$ in LCFS credit due to shifts to overnight and earlier morning charging. Overall, the second financial treatment increases LCFS revenues by $-\$.83$ because it increases midday charging and late evening charging.

Cost of incentives. To determine the financial costs of discounts extended to the participants, we multiply the total energy consumption for both the small and large discount groups throughout the experiment duration by the respective small ($\$.16/kWh$) and large ($\$.23/kWh$) discounts applicable to all charging sessions on the UCSD campus:

$$\triangle Costs \ = (\underbrace{E_l \cdot \ \$.23/kWh}_{Large\ discount}) \ + \ \underbrace{E_s \cdot \ \$.16/kWh}_{Small\ discount}) \tag{5}$$

E_l and E_s refer to the total energy consumption of the large and small discount group, respectively, over the experiment. We assume no financial costs for the informational treatment. For the first financial treatment, the total financial incentives paid to the participants equal \$204.3 for the large and \$124.18 for the small discount. For the second financial treatment, the total financial incentives provided to the participants equal \$243.76 for the large and \$124.9 for the small discount.

IV.B Distributional effects

A common objection to financial incentives for charging sessions is that the benefits are distributed unevenly across socioeconomic groups. Figure VII presents the distributional profile of the financial discounts across six income brackets in our study population. Normalized by group size, the uptake of discounts is uniform across income brackets. However, because EV drivers skew wealthier in our study, high-income households earned the majority of financial discounts for campus charging. While we paid $\$1,667$ in discounts to the highest income group, the lowest income group received only \$216. Given that current EV drivers are wealthier, providing financial incentives to shift these individual's charging sessions to the workplace is a highly regressive policy tool. As the pool of EV drivers becomes more representative of the broader population, this tool should become less regressive.

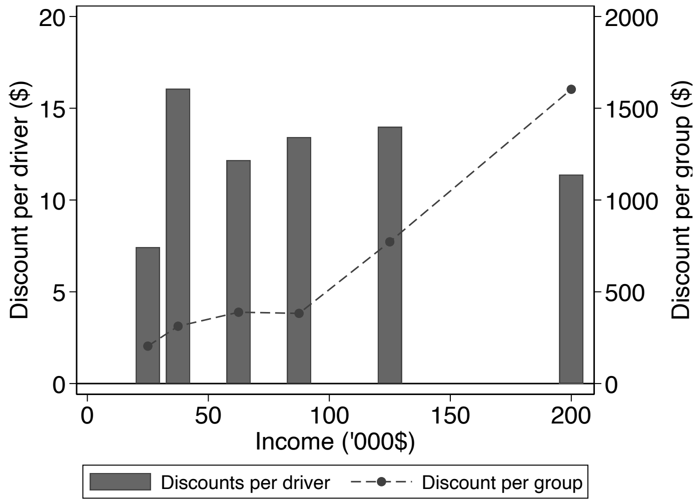


Figure VII: Discounts by income

Notes: This figure shows the discounts paid per driver for each of the six income groups in our study (left axis), and the total discount paid to each income group (right axis). Income is presented at approximately the midpoint of the income brackets. The six groups report incomes (in 000 \$) of $\leq \$25; \$25 - \$50; \$50 - \$75; \$75 - \$100; \$100 - \$150; and > \$150$.

V Conclusion

As the market for new electric cars and trucks increasingly shifts from early to mainstream adopters, who are expected to have less access to private home charging, understanding *where* and *when* these new drivers charge their vehicles is pivotal for addressing their increased energy needs with renewable energy. As electric grids move toward renewable energy, particularly solar, they have large variations in marginal emissions throughout the day. Clean, efficient EV charging in these grids will require temporal shifts toward midday when solar generation peaks and most people are at work. The consequences of failing to shape such a substantial source of future electricity demand are enormous: if charged during daytime, the California EV stock (currently 1.29 million vehicles) would decrease annual emissions by 1.2 $MtCO_2$ compared to overnight charging. This would translate to global avoided damages of \$252 million, assuming a social cost of carbon of 210 $\frac{\$}{tCO_2}$.

The optimal timing of EV charging involves an inherent tradeoff between grid congestion and CO_2 emissions.[33] Currently, grid congestion is the primary concern, which is why electric utilities offer lower rates for nighttime EV charging. However, as more EVs are on the road and renewable energy capacity increases, policies should encourage a shift to daytime

[33]This mirrors congestion-emission tensions in other transportation settings, e.g. congestion zone pricing in city centers (Nilsson et al., 2023).

charging to optimize power usage. Between 2022–23, California curtailed 2.6 million MWh of renewable power, mainly during midday, due to a lack of demand — enough energy for 35 million full charges of an average EV and enough to charge 633,000 EVs (half the California stock) over an entire year.[34]

The empirical findings of our field experiment at UCSD can inform workplace and campus policy aimed at encouraging sustainable daytime charging. The results highlight the importance of environmental knowledge about daytime charging and the limitations of price mechanisms to achieve daytime workplace charging. While our informational prompts and financial discounts did not influence total campus charging, they reshaped total daily charging patterns. Information about the climate benefits of daytime charging prompted a shift in charging from morning toward daytime, better aligning with periods of solar energy generation. In contrast, financial discounts spurred drivers to charge earlier in the morning and later in the evening, outside the optimal period.

Understanding the flexibility of EV charging is vital for developing effective policies and identifying drivers most amenable to these policies. In our experiment, the significant differences among our diverse campus population point to some of these sources of flexibility. Short-distance commuters and students, for example, likely have more flexible schedules due to their shorter commutes or dynamic weekly class schedules, were among the most responsive groups to the information about the benefits of daytime charging, reducing early morning charging. However, students, who are likely to be more price-elastic, were also more likely to shift to overnight charging when given discounts. In contrast, drivers with less flexible schedules, such as long-distance and daily commuters, shifted their charging in more marginal and structured (but still important) ways—e.g., arriving a few hours earlier in the morning when given discounts.

The experiments at the UCSD campus are the start of an evidentiary basis for understanding driver charging behavior at workplaces and how it can be shaped. However, more research is needed to understand how more nuanced discount structures (e.g., time-based or kWh-based) might encourage campus and daytime charging, how to encourage deeper charge sessions to achieve higher network utilization, and how our results generalize to other workplaces. First, the experiment we conducted focused on a college campus, and most non-academic institutions may not face a similar combination of employees, who have mostly set schedules and commutes, and students, who have flexible schedules and live either on or near campus. Second, our study population consists of UCSD affiliates, who drive EVs,

[34] This calculation considers only battery EVs (not plug-in hybrids) and assumes mean vehicle performance (3.5 miles/kWh efficiency, 76 kWh battery size), 14,600 annual driving miles, and mean overnight (22–6) and daytime (9–15) grid carbon intensities of 86.4 and 22.6 gCO_2/MJ, per CARB's LCFS emission attribution methodology that uses average emission factors.

choose to charge at work, and are self-selected in our study – and each of those attributes may entail some selection bias. Consequently, our estimated treatment effects may be higher than for the average population as we expect our subset of early EV adopters to be particularly responsive to the interventions. As many similar institutions are at the forefront of the EV transition, our results should hold reasonably well for these. By tailoring policies to consider the specific composition of drivers and targeting informational campaigns to those most receptive, workplaces can play a pivotal role in fostering sustainable charging practices and mitigating emissions from EV charging.

References

Agency, E. P. (2022). *Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances.*

Agency, E. E. (2021). *New registrations of electric vehicles in Europe.*

Asensio, O. I., M. C. Lawson, and C. Z. Apablaza (2021). "Electric vehicle charging stations in the workplace with high-resolution data from casual and habitual users". *Scientific Data* 8.1, p. 168.

Bailey, M. R. et al. (2023). *Show Me the Money! Incentives and Nudges to Shift Electric Vehicle Charge Timing*. Tech. rep. National Bureau of Economic Research.

Bento, A. M. et al. (2009). "Distributional and efficiency impacts of increased US gasoline taxes". *American Economic Review* 99.3, pp. 667–99.

Bonges III, H. A. and A. C. Lusk (2016). "Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation". *Transportation Research Part A: Policy and Practice* 83, pp. 63–73.

Borenstein, S. (2012). "The redistributional impact of nonlinear electricity pricing". *American Economic Journal: Economic Policy* 4.3, pp. 56–90.

— (2017). "Private net benefits of residential solar PV: The role of electricity tariffs, tax incentives, and rebates". *Journal of the Association of Environmental and Resource Economists* 4.S1, S85–S122.

Borenstein, S., M. Fowlie, and J. Sallee (2021). "Designing electricity rates for an equitable energy transition". *Energy Institute Working Paper* 314.

Bornioli, A., S. Vermeulen, and G. Mingardo (2023). "Can app notifications reduce charging hogging? An experiment with electric vehicle drivers". *Case Studies on Transport Policy*, p. 101143.

Bruegge, C., T. Deryugina, and E. Myers (2019). "The distributional effects of building energy codes". *Journal of the Association of Environmental and Resource Economists* 6.S1, S95–S127.

Burkhardt, J., K. Gillingham, and P. K. Kopalle (2019). *Experimental evidence on the effect of information and pricing on residential electricity consumption.* Tech. rep. National Bureau of Economic Research.

Caperello, N., K. S. Kurani, and J. TyreeHageman (2013). "Do You Mind if I Plug-in My Car? How etiquette shapes PEV driversâ vehicle charging behavior". *Transportation Research Part A: Policy and Practice* 54, pp. 155–163.

Chan, N. W. and K. Gillingham (2015). "The microeconomic theory of the rebound effect and its welfare implications". *Journal of the Association of Environmental and Resource Economists* 2.1, pp. 133–159.

Cronin, J. A., D. Fullerton, and S. Sexton (2019). "Vertical and horizontal redistributions from a carbon tax and rebate". *Journal of the Association of Environmental and Resource Economists* 6.S1, S169–S208.

Davis, B. M. and T. H. Bradley (2012). "The efficacy of electric vehicle time-of-use rates in guiding plug-in hybrid electric vehicle charging behavior". *IEEE Transactions on Smart Grid* 3.4, pp. 1679–1686.

Davis, L. W. (2019). "Evidence of a homeowner-renter gap for electric vehicles". *Applied Economics Letters* 26.11, pp. 927–932.

— (2023). *The Economic Determinants of Heat Pump Adoption*. Tech. rep. National Bureau of Economic Research.

Davis, L. W. and C. R. Knittel (2019). "Are fuel economy standards regressive?" *Journal of the Association of Environmental and Resource Economists* 6.S1, S37–S63.

Dorsey, J., A. Langer, and S. McRae (2022). *Fueling alternatives: Gas station choice and the implications for electric charging*. Tech. rep. National Bureau of Economic Research.

Feger, F., N. Pavanini, and D. Radulescu (2022). "Welfare and redistribution in residential electricity markets with solar power". *The Review of Economic Studies* 89.6, pp. 3267–3302.

Fetene, G. M. et al. (2017). "Myopic loss aversion in the response of electric vehicle owners to the scheduling and pricing of vehicle charging". *Transportation Research Part D: Transport and Environment* 50, pp. 345–356.

Gillingham, K., D. Rapson, and G. Wagner (2020). "The rebound effect and energy efficiency policy". *Review of Environmental Economics and Policy*.

Helmus, J. R., M. H. Lees, and R. van den Hoed (2020). "A data driven typology of electric vehicle user types and charging sessions". *Transportation Research Part C: Emerging Technologies* 115, p. 102637.

International Energy Ageny (2021). *Net zero by 2050*. https://www.iea.org/reports/net-zero-by-2050.

Isenstadt, A. et al. (2022). *Real world usage of plug-in hybrid vehicles in the United States*.

Jabeen, F. et al. (2013). "Electric vehicle battery charging behaviour: findings from a driver survey". In: *Proceedings of the Australasian Transport Research Forum*. Vol. 1.

Kacperski, C. et al. (2022). "Impact of incentives for greener battery electric vehicle charging–A field experiment". *Energy Policy* 161, p. 112752.

Lagomarsino, M. et al. (2022). "Do I need to charge right now? Tailored choice architecture design can increase preferences for electric vehicle smart charging". *Energy Policy* 162, p. 112818.

LaMonaca, S. and L. Ryan (2022). "The state of play in electric vehicle charging services–A review of infrastructure provision, players, and policies". *Renewable and sustainable energy reviews* 154, p. 111733.

Langbroek, J. H., J. P. Franklin, and Y. O. Susilo (2017). "When do you charge your electric vehicle? A stated adaptation approach". *Energy Policy* 108, pp. 565–573.

Lee, J. H. et al. (2020). "Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure". *Transportation Research Part D: Transport and Environment* 79, p. 102249.

McClone, G. et al. (2023). "Hybrid Machine Learning Forecasting for Online MPC of Work Place Electric Vehicle Charging". *IEEE Transactions on Smart Grid.*

Motoaki, Y. and M. G. Shirk (2017). "Consumer behavioral adaption in EV fast charging through pricing". *Energy policy* 108, pp. 178–183.

Newsom, G. (2020). "Executive order N-79-20". *Executive department State of California. Retrieved November* 1, p. 2022.

Nicholas, M. and G. Tal (2015). *Charging for charging at work: increasing the availability of charging through pricing.* Tech. rep.

Nicolson, M. et al. (2017). "Tailored emails prompt electric vehicle owners to engage with tariff switching information". *Nature Energy* 2.6, pp. 1–6.

Nienhueser, I. A. and Y. Qiu (2016). "Economic and environmental impacts of providing renewable energy for electric vehicle charging–A choice experiment study". *Applied energy* 180, pp. 256–268.

Nilsson, P., M. Tarduno, and S. Tebbe (2023). "Road Pricing with Multiple Policy Goals: The Effect on Vehicle Ownership, Driving, and Commuting Distance". *Working Paper.*

Poterba, J. M. (1991). "Is the gasoline tax regressive?" *Tax policy and the economy* 5, pp. 145–164.

Rempel, D. et al. (2022). "Reliability of open public electric vehicle direct current fast chargers". *Human Factors*, p. 00187208231215242.

Sheet, F. (2021). "President Biden Sets 2030 Greenhouse gas pollution reduction target aimed at creating good-paying union jobs and securing US leadership on clean energy technologies". *The White House.*

Sutton, K., S. Hardman, and G. Tal (2022). "Strategies to Reduce Congestion and Increase Access to Electric Vehicle Charging Stations at Workplaces".

Tal, G. et al. (2014). "Charging behavior impacts on electric vehicle miles traveled: who is not plugging in?" *Transportation Research Record* 2454.1, pp. 53–60.

Tal, G. et al. (2020). "Electric cars in California: Policy and behavior perspectives". *Whoâs Driving Electric Cars: Understanding Consumer Adoption and Use of Plug-In Electric Cars*, pp. 11–25.

Wolbertus, R. and R. van den Hoed (2017). "Charging station hogging: A data-driven analysis". In: *The 30th International Electric Vehicle Symposium & Exhibition*.

Appendix

Electric Vehicle Charging at the Workplace:
Experimental Evidence on Incentives and Environmental Nudges

Teevrat Garg *Ryan Hanna* *Jeffrey Myers*
Sebastian Tebbe *David Victor*

A Experimental design

This section provides additional details about EV drivers at the UCSD campus and our recruitment of drivers into the Triton Chargers EV club (Section A.1), the experimental schedule (Section A.2), informational prompts (Section A.3), emails notifying participants about financial discounts (Section A.4), odometer survey (Section A.5), enrollment survey (Section A.6), Clean Air Day (Section A.7), Spring trial informational experiment (Section A.8), and charger scarcity experiment (Section A.9).

A.1 EV drivers at the UCSD campus

EV chargers at the UCSD campus are available for use by UCSD affiliates (faculty, staff, students) and the general public. All charging session data (anonymized) are logged by the charger vendors and may be used by the UCSD Transportation Services Office for operational (non-research) purposes. Available to all drivers, affiliate and public, is the base campus charging rate set by the Transportation Office. During our experiments, the base rate was $\$.30/kWh$ for Level-2 charging.

To promote EVs and help plan transportation electrification at the campus, the Transportation Office offers a 5 $¢/kWh$ discount (17% off the base rate) to affiliates who sign up and provide demographic and home residence information and unique charger vendor identification numbers.

Our team spent about one year recruiting members into a new club for EV-driving affiliates — what we call the "Triton Chargers" EV club. Enrollees agreed to participate in research experiments and respond to surveys and in return receive additional information and discounts on campus charging. To be eligible, drivers must be between 18 and 80 years of age, hold a driver's license valid in California, and be the primary driver of an EV which they intend to keep for at least one year after enrolling. Upon enrollment, drivers respond to a survey about their demographics, EV, charging habits and motivations, and commuting habits (Section A.6). Drivers also respond to recurring (usually twice monthly) surveys that request an odometer reading and updates about their EV (Section A.5). These data allow for estimates of total charging activity. With unique vendor identification numbers (for ChargePoint and PowerFlex), we can analyze each driver's unique campus charging activity as the session level.

A.2 Experimental schedule

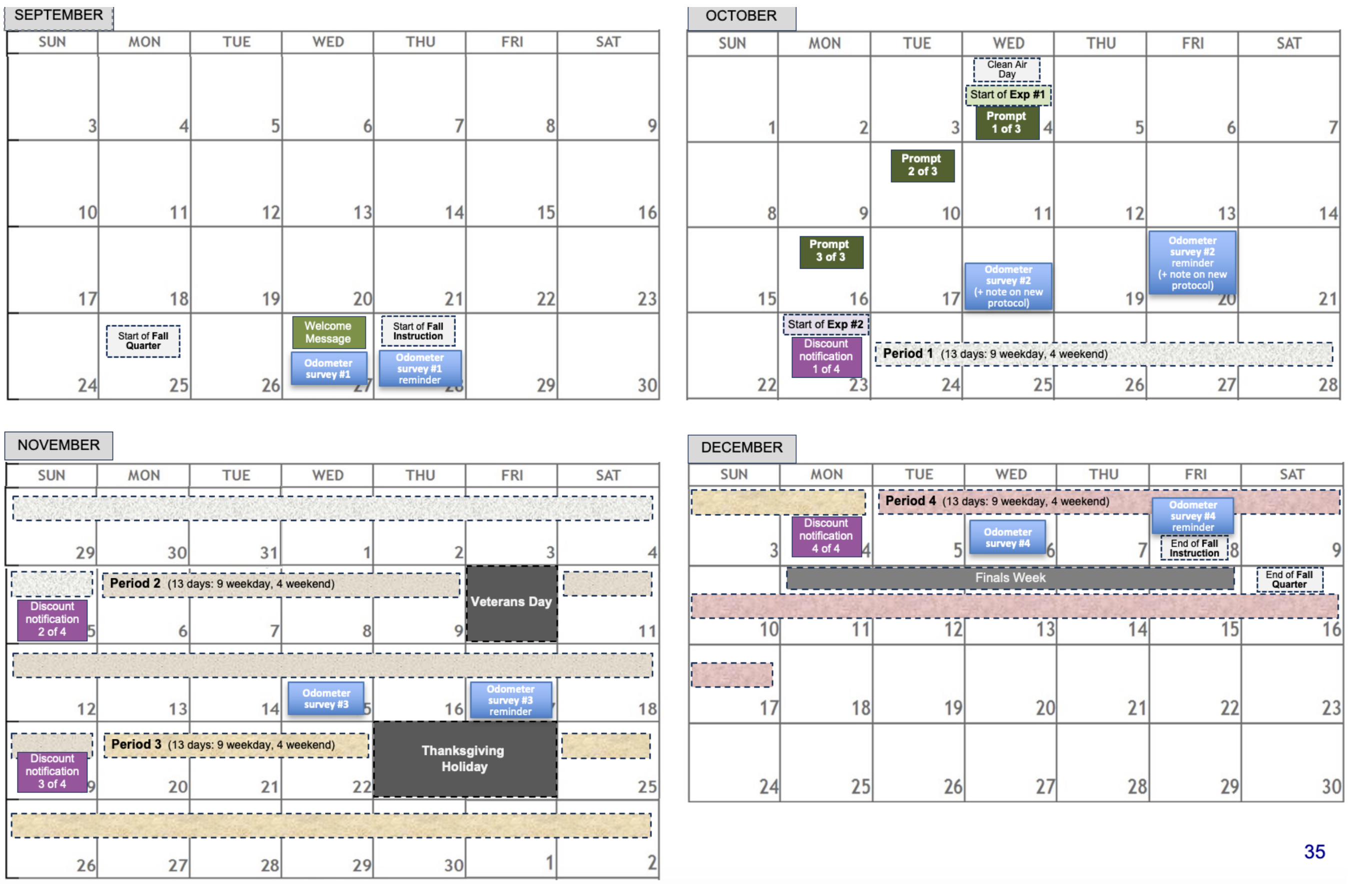


Figure A1: Experimental schedule for the three interventions

Notes: This figure documents the experimental schedule, including dates of all email messages to study participants, prompts, surveys, and relevant holiday and campus dates. The experiment consists of three interventions: an informational (October 4 to October 23), first financial (October 24 to November 5), and second financial (November 6 to November19) intervention. During the informational intervention, the treatment group receives a weekly email message ("Prompt 1 of 3", etc.). Prompts were sent at 6:30 am on the specified day. The Clean Air Day (a non-research campus promotional day) was October 4th; notifications from the Transportation Office were sent to the campus community on the prior day. The first financial intervention is denoted by "Phase 1"; the second, by "Phase 2". Two additional phases (Phases 3 and 4; November 20 to December 17) ensure that drivers in the study have equal access to financial incentives (e.g., so that participants who receive small discounts in Phases 1 and 2 can access large discounts in Phases 3 and 4) but are not part of our analytical experiment.

A.3 Informational prompt

Prior to the experiment, a welcome email (September 27) was sent to all study participants:

- [Welcome Message]: Dear Triton Charger, Welcome back to campus. We write because you have joined the Triton Chargers EV Research Club—are a “Triton Charger”—and agreed to participate in research on EV charging. Starting next week, you will receive another message from us about our first set of research activities for this fall. As you may have seen, there have been a number of changes on campus with parking, EV policies, and costs. Information on UCSD's EV network is maintained here. One of the benefits of being a Triton Charger is that you will have access to additional charging discounts and other information about the benefits of charging on campus. During the fall, you will also receive a few surveys that request odometer readings as well as opportunities to earn prizes. These surveys—one of which we sent today—are very brief (2 questions) but extremely important for our research. We thank you for your participation. If at any time you have questions about this research study or EV charging on campus, please do not hesitate to contact us. Learn more about the Triton Chargers club here.

The treatment in the informational experiment consists of an emailed prompt (text below) and the infographic (Figure A2):

- [Informational prompts]: In San Diego in fall, charging a typical EV during daytime, when solar power is plentiful, avoids **29** pounds of CO_2 emissions compared to charging during nighttime when California relies heavily on burning natural gas to generate electricity. This is equivalent to avoiding burning **1.5** gallons of gasoline with every charge; scientists estimate that these avoided CO_2 emissions prevent **$2.75** in costs to human welfare and the global economy.

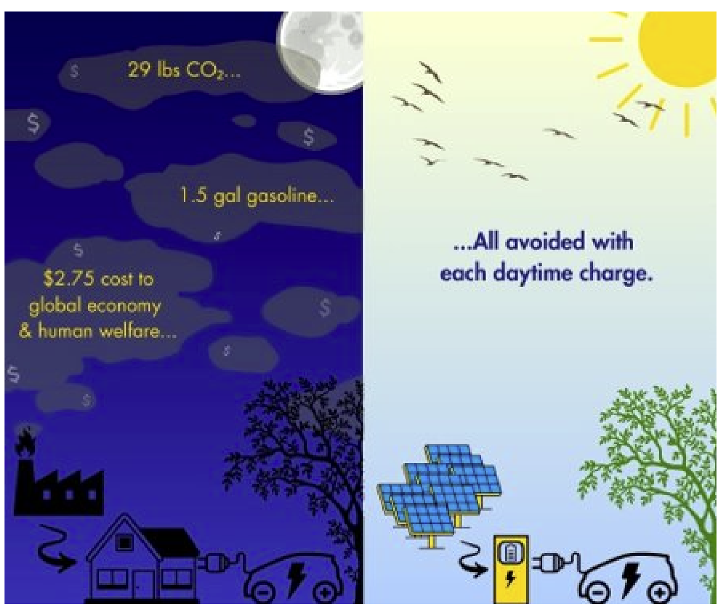


Figure A2: Infographic included with the informational prompt

As part of informational prompt, we calculate CO_2 emissions avoided, the gasoline equivalent of those CO_2 emissions, and global environmental damages avoided from shifting from nighttime to daytime charging in California. We calculate avoided emissions from charging during daytime compared to nighttime as the difference in emissions between an archetypal daytime and nighttime session:

$$Emissions\ avoided \ = \ Emission_{night} \ - \ Emission_{day} \ = \ CI_{night} \cdot E – CI_{day} \cdot E,$$

where $CI_{night} = 87\, gCO_2/MJ$ and $CI_{day} = 15\, gCO_2/MJ$ is the mean carbon intensity of the power grid (per CARB's LCFS program methodology; see Table B4) during nighttime and daytime during the period of our experiments (quarter 4), and E is the energy consumed during the charge session. In our calculation we assume a 75% fill-up of a Tesla Model 3 with a 68-kWh battery (51 kWh in total) over 4 hours (12 am to 4 am for nighttime; 8 am to 12 pm for daytime). Thus, the emissions avoided by shifting from nighttime to daytime EV charging, expressed as avoided CO_2, is

$$(87 - 15)\ \frac{gCO_2}{MJ} \cdot 51kWh \cdot 3.6MJ/kWh \cdot 2.2lb/kg = \ 29lbCO_2$$

The gasoline equivalent (in gallon) associated with these avoided CO_2 emissions is given by

$$Gasoline\ equivalent \ = \ Emissions\ avoided \cdot CO_2\ content\ of\ gasoline,$$

where one gallon of gasoline, combusted, produces 19.4 pounds of CO_2. The gasoline equivalent when shifting from nighttime to daytime EV charging is

$$29lbCO_2 \cdot \frac{1}{19.4\frac{lbCO_2}{gal}} \ = \ 1.5\, gallons$$

The global environmental damages avoided (in \$) due to avoided CO_2 is given by

$$Damages\ avoided \ = \ Emissions\ avoided \cdot \ SCC,$$

where we assume the social cost of carbon (SCC) is 210 $\frac{\$}{tCO_2}$ following estimates from the U.S. Environmental Protection Agency (2022). The average monetary damages when shifting from nighttime to daytime EV charging is

$$29\, lbCO_2 \cdot \ \ (1kg\, /\, 2.2lb) \cdot (1t\, /\, 1000kg)\ 210\frac{\$}{tCO_2} \ = \ \$2.75$$

A.4 Prompts for the financial discounts

Research participants were notified about financial discounts via email. On October 23, ahead of the first financial treatment, the following messages were sent to the large and small discount treatment arms:

- [Large discount group]: **From October 24 through November 5**, we will offer a >**75%** discount on all Level-2 charging you do on campus. We are providing a **$0.23/kWh** discount on the base campus price of $0.30/kWh. That means you pay just **$0.07/kWh**. After November 5, these discounts will continue, but they may change in size. We will tell you of all changes ahead of time.
- [Small discount group]: **From October 24 through November 5**, we will offer a >**50%** discount on all Level-2 charging you do on campus. We are providing a **$0.16/kWh** discount on the base campus price of $0.30/kWh. That means you pay just **$0.14/kWh**. After November 5, these discounts will continue, but they may change in size. We will tell you of all changes ahead of time.

On November 5, ahead of the second financial treatment, the following messages were sent to the large–large, large–small, and small–small discount treatment arms:

- [Large - large discount group]: In October, we announced discounted campus charging through November 5. **From November 6 through November 19, your discount will remain the same.** The Triton Chargers research team will continue to provide a >**75%** discount ($0.23/kWh) off the base campus price of $0.30/kWh. That means you will continue paying just **$0.07/kWh**. After November 19, these discounts will continue, but they may change in size. We will tell you of all changes ahead of time.
- [Large - small discount group]: In October, we announced discounted campus charging through November 5. **From November 6 through November 19, your discount will now be smaller.** It will decrease from about 75% to **50%** off the campus's base price of $0.30/kWh. That means you will now pay just **$0.14/kWh**. After November 19, these discounts will continue, but they may change in size. We will tell you of all changes ahead of time.
- [Small - small discount group]: In October, we announced discounted campus charging through November 5. **From November 6 through November 19, your discount will remain the same.** The Triton Chargers research team will continue

to provide a >**50%** discount ($0.16/kWh) off the base campus price of $0.30/kWh. That means you will continue paying just **$0.14/kWh**. After November 19, these discounts will continue, but they may change in size. We will tell you of all changes ahead of time.

Similar messages were sent for Phases 3 and 4 (Section A.2), though these were not part of the analytical experiment.

A.5 Odometer survey

Odometer surveys were sent to all participants via email and with the following message:

- As part of ongoing EV research at UCSD, please help us by completing a very brief 2-question survey on your current odometer reading. Odometer readings are important because they help us better understand how you are using the campus EV network to meet your charging needs. As a reminder, we are sending a few surveys over the Fall quarter. By responding to at least two, you will be entered into a raffle for one of three $1,000 Visa gift cards, drawn at the end of the quarter. For each additional survey returned beyond the two, you will receive an additional two raffle tickets.

Odometer

1. What is the current odometer reading on your primary EV or plug-in hybrid? Please round to the nearest mile.

- [Open response]

2. Please take a photo of the odometer on your vehicle dashboard and upload it here. (You have 7 days to complete this survey. If you are not currently in your vehicle, you can pause the survey and return later.)

Electric vehicle

3. In the last 2 weeks, have you changed the primary EV or plug-in hybrid that you drive?

- a. No, I drive the same vehicle most of the time.
- b. Yes, I no longer drive an EV or plug-in hybrid.
- c. Yes, I now drive a different EV or plug-in hybrid most of the time.

3a. [If 3 == c] What is the primary electric vehicle or plug-in hybrid that you currently drive?

- a. Year [Drop-down list]
- b. Make [Drop-down list]
- c. Model [Drop-down list]
- d. Type [Drop-down list]

A.6 Triton Chargers EV Club enrollment survey

The following is our question list for the Triton Chargers Enrollment Survey.

Intro & Contact

1. Please fill out your contact information

- First Name [Open response]
- Last Name [Open response]
- UCSD email address [Open response]
- Cellphone number [Open response]

2. [Consent form to act as a research subject]

Work/School

3. What is your UCSD status? (If you are a student employee, choose student.)

- a. Undergraduate student
- b. Graduate or post-graduate student (Master's, PhD, post-doc)
- c. Faculty
- d. Staff
- e. Other

4. While on campus for work or school, which building(s) are you primarily located in?

- a. [Drop-down list]

Residence

5. Please enter the 5-digit zip code where you live.

- a. [Open response]

6. Which of the following best describes your home living arrangement?

- a. I own a single-family house
- b. I rent a single-family house
- c. I own a condo
- d. I rent a unit in an off-campus, multi-unit complex (e.g. an apartment, condo)
- e. I live in UCSD campus housing, (e.g. undergraduate, graduate, faculty)
- f. Other [open response]

6a. [If 6 == e] If you live on campus, which building/complex do you live in?

- a. [Drop-down list]

7. Do you have access to EV charging at your residence?

- a. [Yes / No / I don't know]

7a. [If 7 == yes] If you have access to charging at your residence, what type of charger do you have access to?

- a. Level 1 (110V or 120V—requires no specially installed hardware)
- b. Level II (240V—uses a small box attached to the wall, typically installed by an electrician, and can charge the car overnight)
- c. DC Fast Charger (480V or 500V—uses a large box installed by an electrician that can charge the car in an hour or two; rare at residences)
- d. One of these, but I am not sure which one

b. [If 7 == No] If you do not have dedicated charging at your residence, how likely are you to purchase a home charger in the next 12 to 18 months (assuming such an option is available to you)?

- a. Extremely unlikely

- b. Somewhat unlikely
- c. Neither likely nor unlikely
- d. Somewhat likely
- e. Extremely likely

Car

8. What is the primary vehicle or plug-in hybrid that you drive? (If your specific make-model- year-type is not shown, please select "other" for all four dropdown.)

- a. Year [Drop-down list]
- b. Make [Drop-down list]
- c. Model [Drop-down list]
- d. Type [Drop-down list]

Commuting and Charging Habit and Preferences

9. During the **Spring 2023 academic quarter,** how often per week do you expect to commute to campus from offsite using your electric vehicle or plug-in hybrid?

- a. Less than once per week
- b. 1 day per week
- c. 2 days per week
- d. 3 days per week
- e. 4 days per week
- f. 5 days per week
- g. More than 5 days per week
- h. I don't commute because I live on campus

10. In a typical week, what percentage of your charging do you do at the following locations?

- a. My residence [0–100% slider]
- b. Neighborhood charging plaza within half a mile from my residence [0–100% slider]

- c. Someone else's home or residence [0–100% slider]
- d. Destinations (e.g., malls, restaurants, etc.) [0–100% slider]
- e. UCSD campus [0–100% slider]
- f. Other (e.g., freeways, dedicated charging plazas) [0–100% slider]

[Implemented with sliders and a permissive checksum.]

11. On a typical weekday (Monday–Thursday), what percentage of your charging do you do at the following times of day?

- a. Morning (6am–12pm) [0–100% slider]
- b. Afternoon (12–4pm) [0–100% slider]
- c. Evening (4–9pm) [0–100% slider]
- d. Night (9pm–5am) [0–100% slider]

[Implemented with sliders and a permissive checksum.]

12. At the place and time where you most commonly charge, what rate do you pay?

- a. I don't know
- b. I have free charging
- c. $0.01–$0.04 cents per kilowatt hour
- d. $0.05–$0.09 cents per kilowatt hour
- e. $0.10–$0.13 cents per kilowatt hour
- f. $0.14–$0.17 cents per kilowatt hour
- g. $0.18–$0.21 cents per kilowatt hour
- h. $0.22–$0.24 cents per kilowatt hour
- i. $0.25–$0.29 cents per kilowatt hour
- j. $0.30–$0.39 cents per kilowatt hour
- k. $0.40–$0.49 cents per kilowatt hour

- l. \$0.50–\$0.59 cents per kilowatt hour
- m. \$0.60–\$0.69 cents per kilowatt hour
- n. \$0.70 or more per kilowatt hour

13. When contemplating when and where to charge in the city (ie. at home, on campus, elsewhere), consider the factors that have the biggest impact on your decision. Which of the following most apply to you? Drag the bars or type in the boxes at the end to allocate 100 points among the options below.

- a. I charge when or where charging rates (i.e. prices) are the lowest
- b. I charge where and when I think I am most likely to find an open and working charging stall.
- c. I charge where and when it helps me get more convenient parking.
- d. I charge at stations closest to my daily activities.
- e. I charge when and where I know charging will be quickest (e.g., at DC Fast Chargers).
- f. I charge when and where I think the environmental impact will be the lowest.
- g. I don't have much choice; I charge on campus because it's the only convenient charging option available to me

14. When you charge on the UCSD campus, independent of where you actually end up charging, what is your preferred on-campus charging location?

- a. Central campus (Gilman parking garage, School of Medicine)
- b. East campus (Athena parking garage, Medical Center, Skaggs)
- c. Graduate housing (One Miramar, Mesa Nuevo, Nuevo West, South Mesa, etc.)
- d. North campus (Hopkins parking garage, Pangea parking garage, Rady School of Management)
- e. Scripps Institution of Oceanography campus
- f. South (Osler) parking garage
- g. None; I prefer not to charge on campus

- h. Other

15. **If/when you decide to charge on campus**, consider the factors that have the biggest impact on your decisions about when and where **at UCSD** to charge. Which of the following most apply to you? Drag the bars or type in the boxes at the end to allocate 100 points among the options below.

- a. I charge where and when I think I am most likely to find an open charging stall (e.g. I arrive early in the morning when there are more open stalls).
- b. I charge wherever is closest to my office, lab, or classroom.
- c. I prefer to charge at stations where the allowed stall dwell time is longest, to reduce the need to move my car or get a ticket for exceeding the limit.
- d. I prefer to charge for a short period of time (e.g. using fast charging) and then depart
- e. I prefer to charge when and where I think the environmental impact will be the lowest

Demographics

16. Choose one or more races that you consider yourself to be

- a. White or Caucasian
- b. Black or African American
- c. American Indian/Native American or Alaska Native
- d. Asian
- e. Native Hawaiian or Other Pacific Islander
- f. Other
- g. Prefer not to say

17. Are you of Hispanic or Latino origin?

- a. [Yes / No]

18. What was your total household income before taxes during the past 12 months?

- a. Less than $25,000
- b. $25,000–$49,999
- c. $50,000–$74,999
- d. $75,000–$99,999
- e. $100,000–$149,999
- f. $150,000 or more
- g. Prefer not to say

19. What is your age?

- a. 18–25
- b. 26–35
- c. 36–45
- d. 46–55
- e. 56–65
- f. 66–75
- g. 75+ 20.

What is your gender?

- a. Female
- b. Male
- c. Other/Non-binary

21. What is the highest level of education you have completed?

- a. Some high school or less
- b. High school diploma or GED
- c. Some college, but no degree
- d. Associates or technical degree

- e. Bachelor's degree
- f. Master's degree (MA, MS, MBA)
- g. Advanced professional degree (PhD, JD, MD, etc.)

EVCC member
22. Are you already a member of the campus EV Charging Club?

- a. [Yes / No / I'm not sure]

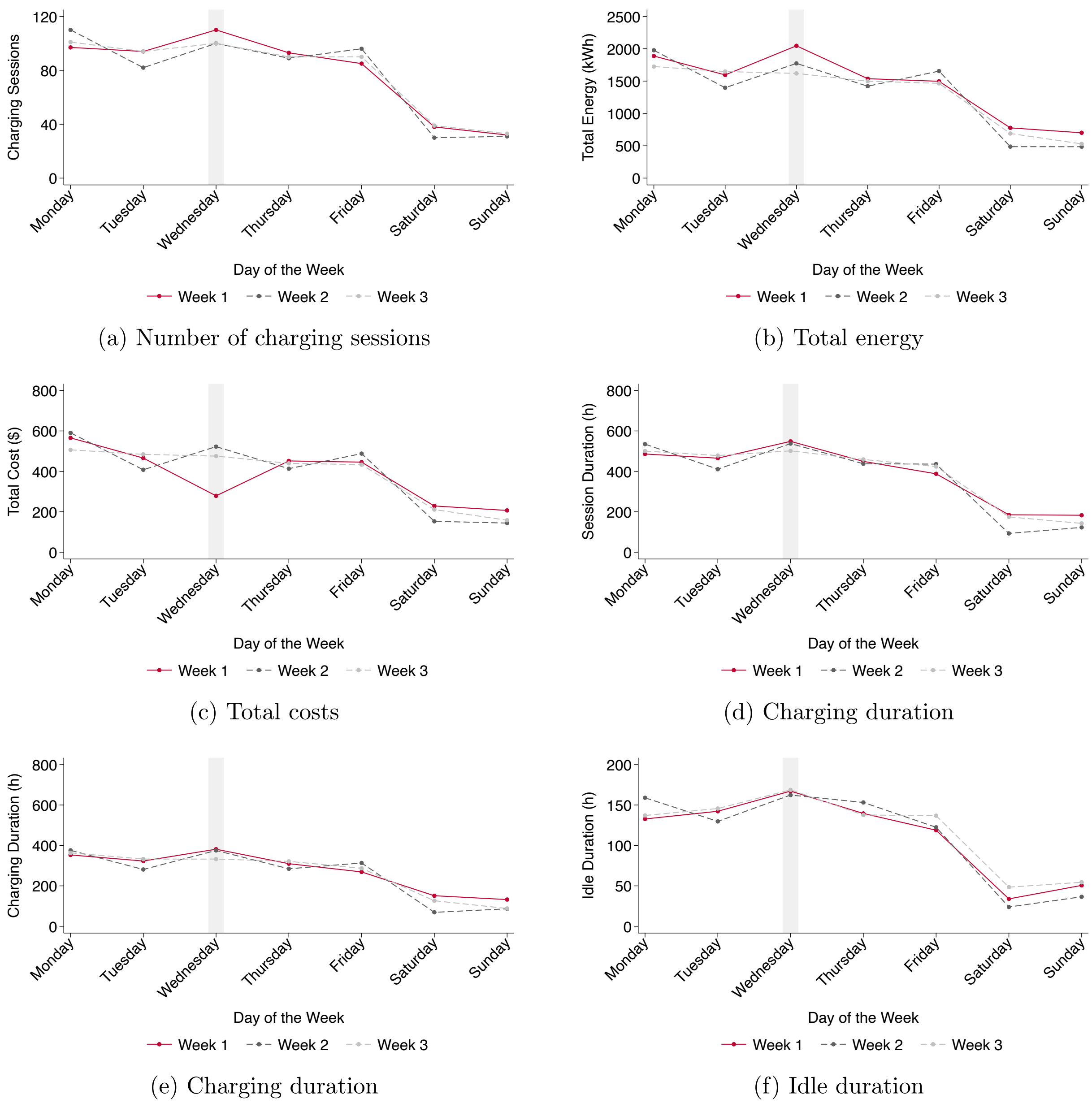
Charging Accounts
23. Click here to set up your ChargePoint account if you don't yet have one or to log in if you do. Enter your ChargePoint ID below.

- a. [Open response]

24. Click here to set up your PowerFlex account and download the Smartphone app if you haven't yet. Enter the email address associated with your PowerFlex account below.

Open Response
Do you have any final comments on the EV charging experience at the UCSD campus? [Open response]

A.7 Clean Air Day



(a) Number of charging sessions

(b) Total energy

(c) Total costs

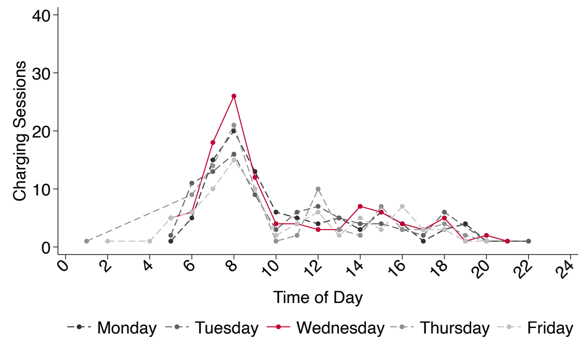
(d) Charging duration

(e) Charging duration

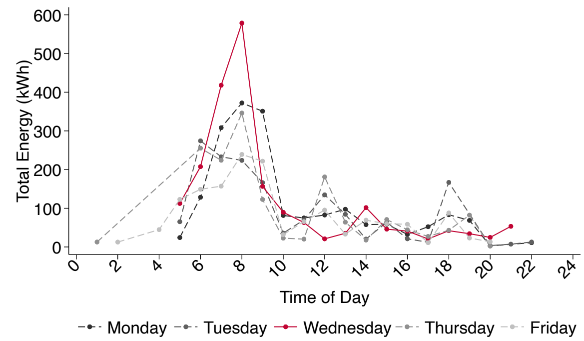
(f) Idle duration

Figure A3: Charging activity on the Clean Air Day by day of the week

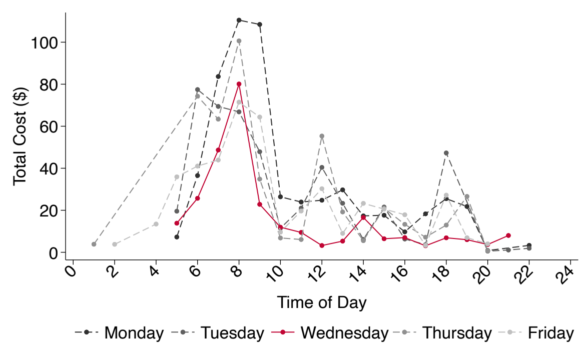
Notes: This figure shows the charging activity of the Triton Chargers EV club during the first three weeks of October by day of the week. Shown are the number of charging sessions (Panel A), energy consumed (Panel B), session cost (Panel C), session duration (Panel D), charging duration (Panel E), and idle duration (Panel F). Weeks 1 to 3 correspond to October 2-8 (red), October 9-15 (gray), and October 16-22 (light gray). The Clean Air Day was the Wednesday, October 4 (week 1). "Session duration" denotes the full plug-in duration; "charging duration" the duration of active charging; and "idle duration" the duration parked but not charging.



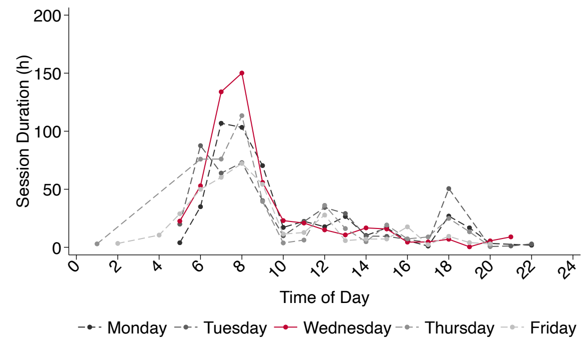
(a) Number of charging sessions



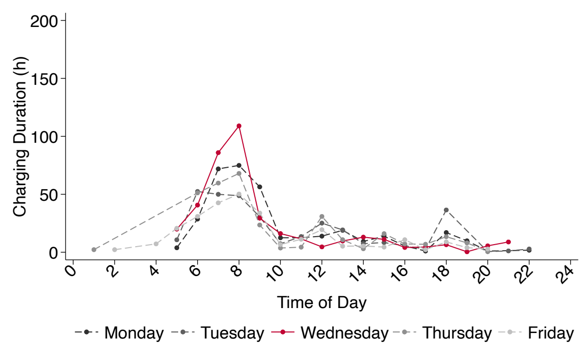
(b) Total energy



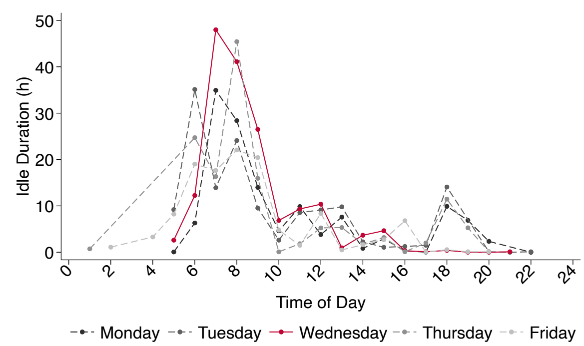
(c) Total costs



(d) Charging duration



(e) Charging duration



(f) Idle duration

Figure A4: Charging activity on the Clean Air Day by time of day

Notes: This figure shows the charging activity of the Triton Chargers EV club during the first week of October (October 2-8) by time of day. Shown are the number of daily charging sessions (Panel A), energy consumed (Panel B), session cost (Panel C), session duration (Panel D), charging duration (Panel E), and idle duration (Panel F). The Clean Air Day (denoted in red) was Wednesday, October 4. "Session duration" denotes the full plug-in duration; "charging duration" the duration of active charging; and "idle duration" the duration parked but not charging..

A.8 Spring trial informational experiment

In June 2023, about four months before the start of our core experiment, we ran a "trial" informational intervention, i.e. a scaled-down version of the full intervention we ran in the fall. This scaled-down trial was shorter in duration and had fewer participants but used the same methodology and structure: the Triton Chargers EV club enrollment survey, stratified black randomization into treatment and control groups, and informational treatment consisting of an email message about the climate benefits of daytime EV charging.

The experimental schedule of the spring trial experiment is documented in Figure A5. On May 31, all participants received a welcome message to the Triton Chargers EV club. The treatment and control groups received four informational prompts between June 6 and June 14, as follows:

- [Treatment]: Thank you for being a Triton Charger and supporting research aimed at improving the quality of charging services offered at UCSD. We are working to grow our charging network and reduce automobile emissions as we transition to an electric vehicle future. In San Diego in spring, charging a typical EV during daytime, when solar power is plentiful, avoids **26** pounds of CO_2 emissions compared to charging during nighttime. This is equivalent to avoiding burning **1.4** gallons of gasoline with every charge. In addition, scientists estimate that these avoided CO_2 emissions prevent **$2.50** in costs to human welfare and the global economy.

- [Control] Thank you for being a Triton Charger and supporting research aimed at improving the quality of charging services offered at UCSD. We are working to grow our charging network as we transition to an electric vehicle future.

In addition, we conducted two surveys that request an odometer reading and updates about drivers' EV. These data allow for estimates of total charging activity.

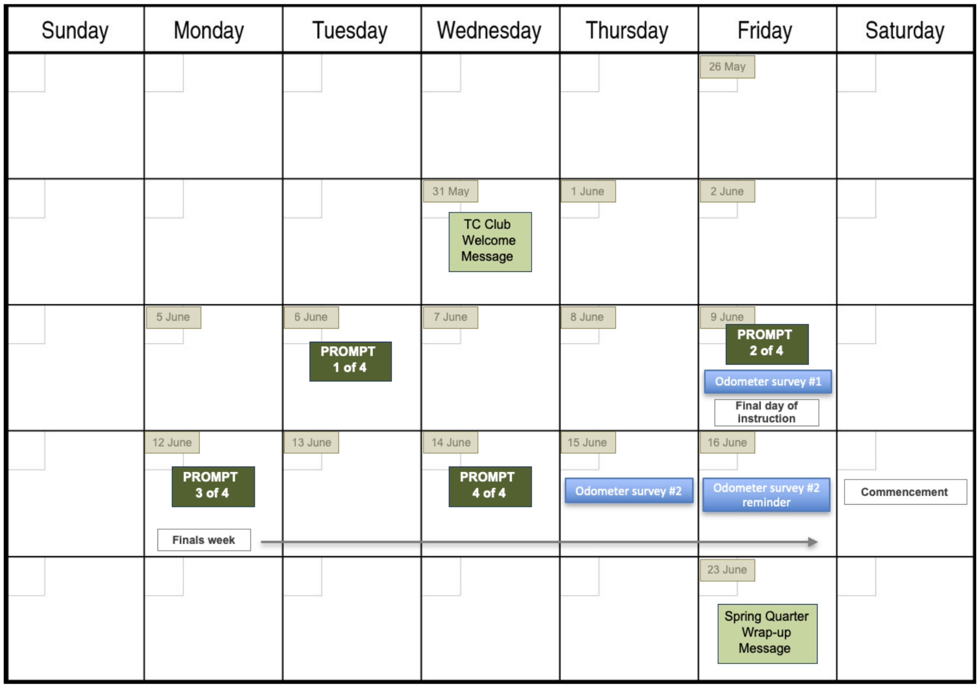


Figure A5: Experimental schedule for the spring trial experiment

Notes: This figure shows the schedule of the spring trial experiment. The treatment group receives a bi-weekly email message ("Prompt 1 of 4", etc.). The control group receives a generic thank-you message. Prompts are sent at 6.30 am on the specified day. All participants receive two odometer surveys.

Table A1: Regression analysis of spring trial

	OLS						
	(1) Share	(2) N(Charging)	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Spring Trial Experiment							
Info. Prompt	-.020	-.467	-4.418	-1.525	-400.533*	-112.891	-287.641*
	(.153)	(.313)	(8.903)	(1.851)	(213.941)	(111.904)	(153.761)
%-Effect	-7.7	-26.98	-8.09	-13.43	-36.72	-17.2	-66.23

Notes: This table presents the regression estimates of the spring trial informational intervention(Panel A). The outcome variables indicate the share of campus charging (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The %-effects is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

A.9 Charger scarcity experiment

Four months after our series of informational and financial experiments, we ran a follow-up intervention over 13 days from February 5 to 17 to test for perceived scarcity in available chargers. In this intervention, we varied the discount notification messages that drivers received, such that messages indicated that different numbers of drivers would receive the discount.

This follow-up experiment mimicked phase 1 of the financial experiment: the same methodology, same participants (i.e., new club enrollees were excluded), stratified block randomization into treatment arms that receive small or large discounts, notifications, and odometer surveys. The experimental schedule of the spring trial experiment is documented in Figure A6.

In total, the experiment consisted of four treatment arms. Two arms received the large discount; two received the small. New to this experiment was that, within each discount regime, half of participants received a discount notification email that indicated that all drivers would receive the discount simultaneously, while the other half received a discount notification message that indicated that no more than 33% of drivers would receive the discount, as follows:

- [High scarcity]: Starting tomorrow, and for the next two weeks, you will receive an extra discount on campus charging for being a member of the Triton Chargers EV club. During these two weeks, **we are making discounts available to you and fellow Triton Chargers.**
- [Low scarcity]: Starting tomorrow, and for the next two weeks, you will receive an extra discount on campus charging for being a member of the Triton Chargers EV club. During these two weeks, **you and no more than 33% of Triton Chargers will receive this discount.**

Through this intervention, we explicitly sought to influence the percieved availability of discounts, and thus the perceived likelihood of discount-induced scarcity for campus charging.

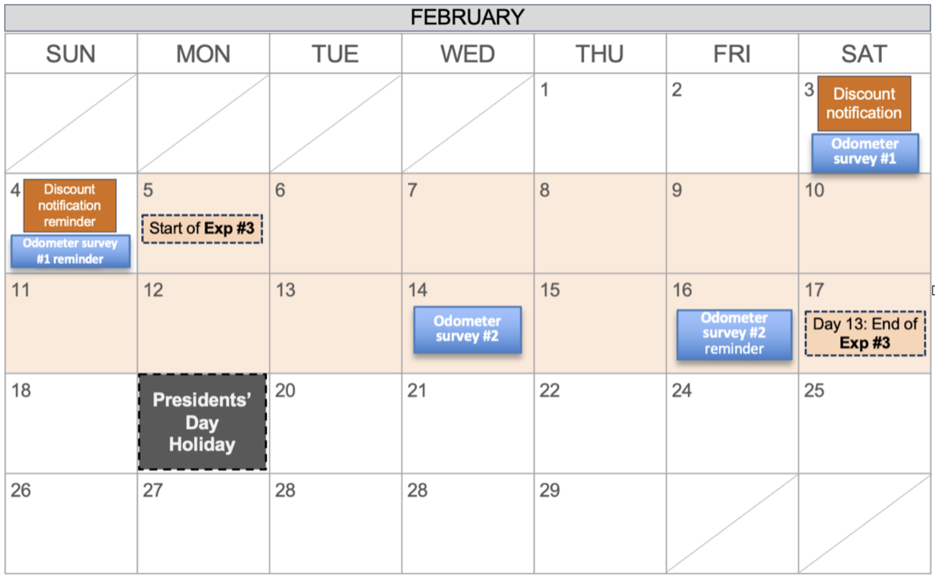


Figure A6: Experimental schedule for the scarcity experiment

Notes: This figure shows the schedule of the charger scarcity experiment (February 5 to 17). The experiment consists of two treatment arms: a financial and a induced scarcity intervention. During the financial treatment, participants receive either a small or large discount on campus charging. During the scarcity intervention, participants were told that 33% or all Triton chargers received the discounts.

B Supplementary data

B.1 UCSD EV charging network

UCSD has installed three distinct types of EV parking stalls (Figure B1) across its campus (Figure B2) that differ in charger type and parking rules (Table B1).[35]

1. EV-1 indicates a 1-hour parking limit at a DC fast charger (DCFC) that delivers 50–125 kW, adds 75–185 miles of range per 30 minutes, and uses CHAdeMO or CCS plugs. EV-1 spaces have no energy minimum, but drivers should initiate a charging session and move their vehicles immediately after the session.

2. EV-4 indicates a 4-hour parking limit at a level-2 charger that delivers 6.6 kW, adds 21 miles of range per hour, and uses a J1772 plug. EV-4 spaces require a minimum 7-kWh charge. Vehicles may remain in the stall (charging or idling) for up to four hours.

3. EV-12 indicates a 12-hour parking limit at a level-2 charger that delivers 1.2–6.6 kW (some leverage circuit-sharing and operate at a continuous 3.3 kW), adds up to 21 miles of range per hour, and uses a J1772 plug. EV-12 spaces require a minimum 10-kWh charge. Drivers enter their planned departure time and desired miles of range to be added; the charger optimizes power delivery to balance the needs of the EV and power grid.

A valid UCSD parking permit or hourly parking payment is required to park in campus EV charging stalls. Drivers may be cited if they park in an "EV Charging Only" stall but are not actively charging or exceeding the posted time limit and are not actively charging. The university plans to install an additional 760 Level-2 chargers and 35 DCFCs by year-end 2025.

[35] See https://transportation.ucsd.edu/commute/ev-stations.html for more information about EV charging stalls at UCSD.

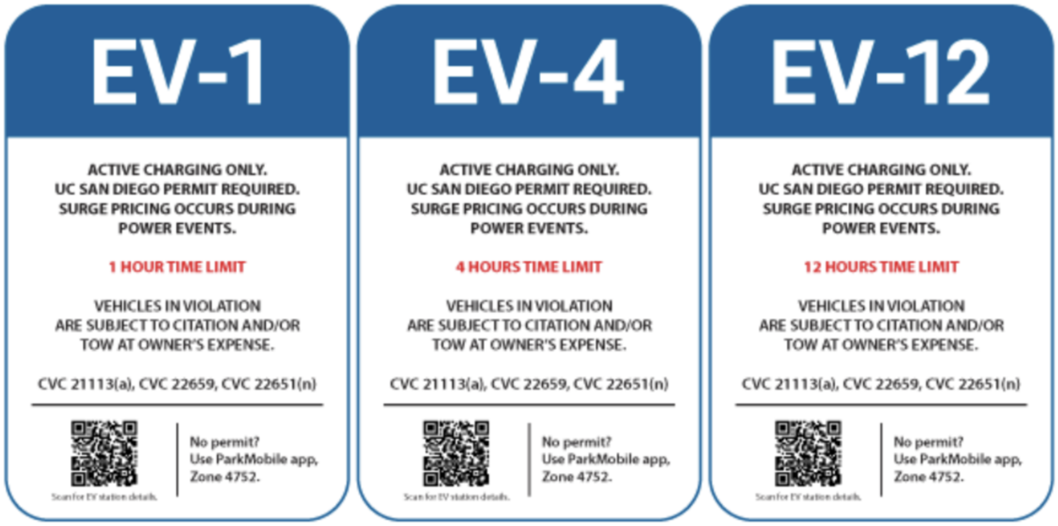


Figure B1: Type of parking stalls at UCSD

Notes: This figure displays the three types of parkings stalls at the UCSD campus.

Table B1: Parking stalls rules and features

	Tariff		
	EV -1	EV -4	EV 12
Limit	1 hour	4 hours	12 hours
Ports	1	2	1
Power	50–125 kW	6.6 kW	1.2–6.6 kW
Range	75—185 mi per half hour	21 mi per hour	21 mi per hour
Plugs	CHAdeMO, CCS	J1772	J1772
Energy minimum	None	7 kWh	10 kWh
Flex charging	No	No	Yes

Notes: This table summarizes the parking rules and features at the UCSD campus.

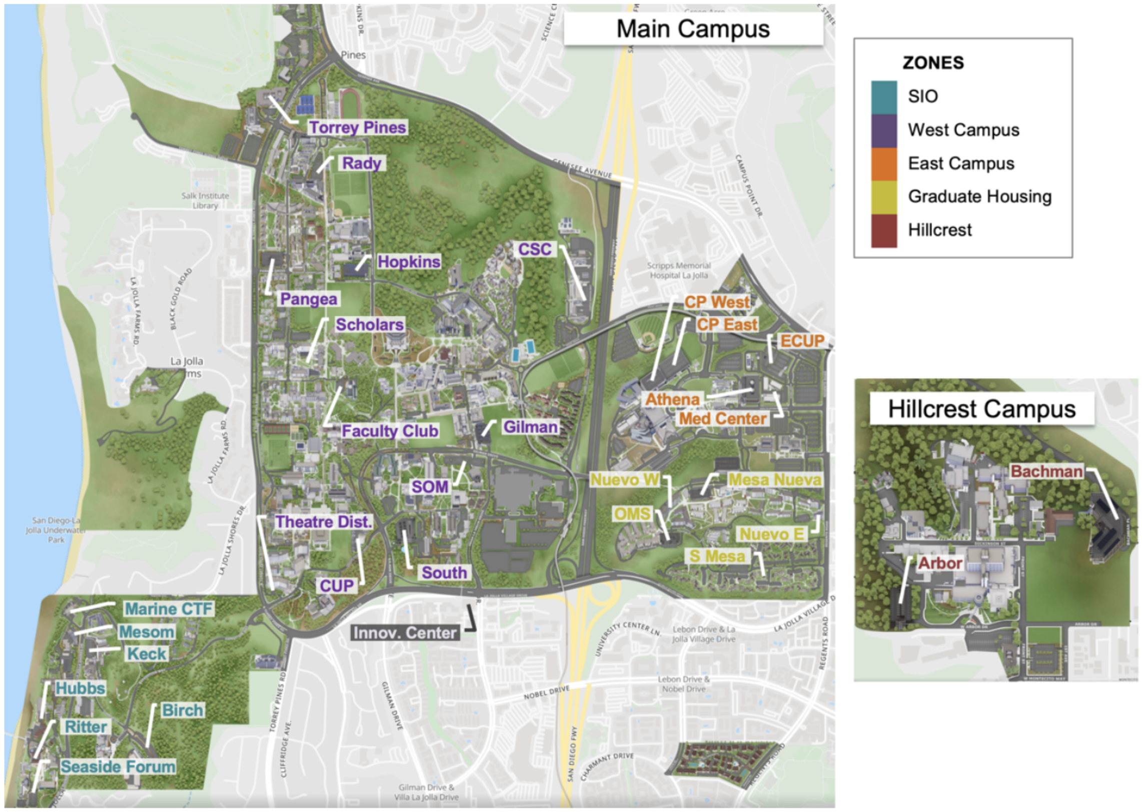


Figure B2: Parking zones and plazas at UCSD

Notes: This figure shows the five distinct parking zones and individual plazas and garages on the UCSD campus. Blue-green denotes the Scripps Institution of Oceanography (SIO); purple, West Campus; orange, East Campus; yellow, Graduate Housing; and red, Hillcrest Medical Center. The Hillcrest Campus is geographically separate from the Main Campus.

B.2 SDG&E EV charging rates

Table B2: SDG&E residential EV charging rates (October–November 2023)

	Price ($\$/kWh$)					
	Summer (Jun-Oct)			Winter (Nov-May)		
Tariff	Super-Off-Peak	Off-peak	On-peak	Super-Off-Peak	Off-peak	On-peak
EV -TOU	.285	.497	.832	.276	.464	.527
EV -TOU-2	.285	.497	.832	.276	.464	.527
EV -TOU-5	.154	.481	.816	.145	.448	.511

Notes: This table presents SDG&E residential rates by tariff period (super-off-peak, off-peak, and on-peak) for the summer and winter seasons. Super-off-peak hours are 12am - 6am; off-peak hours, 6am - 4pm and 9pm - 12am; and on-peak hours, 4pm - 9pm. The EV-TOU tariff requires a separate EV meter, installed by an electrician at the homeowner's expense, that tracks EV electricity use separately, while the house remains on a tiered rate. EV-TOU-2 and EV-TOU-5 use an existing household smart meter to track both home and EV electricity use. EV-TOU-5 has lower volumetric rates (the lowest rates for overnight EV home charging) along with a fixed monthly fee of $16. Homeowners with household solar PV or battery storage might have different rates.

Table B3: SDG&E public retail EV charging rates (October–November 2023)

Time of day	Price ($\$/kWh$)
12:01 - 01:00	.56
01:01 - 02:00	.28
02:01 - 03:00	.28
03:01 - 04:00	.28
04:01 - 05:00	.28
05:01 - 06:00	.28
06:01 - 07:00	.29
07:01 - 08:00	.28
08:01 - 09:00	.26
09:01 - 10:00	.25
10:01 - 11:00	.24
11:01 - 12:00	.24
12:01 - 13:00	.24
13:01 - 14:00	.25
14:01 - 15:00	.25
15:01 - 16:00	.27
16:01 - 17:00	.29
17:01 - 18:00	.31
18:01 - 19:00	.32
19:01 - 20:00	.31
20:01 - 21:00	.30
21:01 - 22:00	.30
22:01 - 23:00	.29
23:01 - 24:00	.29

Notes: This table presents mean hourly prices for SDGE's Power Your Drive public charging program during the first and second financial treatment (October 1 - November 30). Retail rates reflect wholesale electricity prices, which change hourly, and are available at public chargers participating in the Power Your Drive program.

B.3 Power grid carbon intensity

Table B4: Average carbon intensity (gCO2/MJ) of the California power grid

	Season			
Time	2022-Q1	2022-Q2	2022-Q3	2022-Q4
12:01 - 01:00	81.66	82.48	85.43	90.97
01:01 - 02:00	81.62	80.68	82.43	87.1
02:01 - 03:00	81.62	80.64	81.82	84.95
03:01 - 04:00	81.62	80.61	81.59	84.52
04:01 - 05:00	81.62	81.79	81.47	86.37
05:01 - 06:00	87.03	90.14	83.5	97.52
06:01 - 07:00	108.88	88.8	94.67	119.41
07:01 - 08:00	107.18	28.24	90.9	118
08:01 - 09:00	63.59	2.28	57.31	97.07
09:01 - 10:00	29.08	1.68	7.05	38.86
10:01 - 11:00	0.41	3	12.26	31.13
11:01 - 12:00	0	47.2	20.61	7.57
12:01 - 13:00	0	50.24	30.4	9.03
13:01 - 14:00	0	52.09	42.67	11.27
14:01 - 15:00	0	55.64	52.49	40.08
15:01 - 16:00	28.52	60.37	99.35	74.02
16:01 - 17:00	63.34	26	104.51	123.7
17:01 - 18:00	105.37	30,.28	129.55	144.16
18:01 - 19:00	136.85	75.05	141.37	147.13
19:01 - 20:00	131.9	146.13	148.42	143.16
20:01 - 21:00	121.95	147.19	140.49	136.57
21:01 - 22:00	101.6	124.86	119.97	122.34
22:01 - 23:00	87.84	94.26	102.34	108.95
23:01 - 24:00	82.13	84.41	91.01	95.2

Notes: The table presents the California Air Resources Board (CARB) Low Carbon Fuel Standard (LCFS) quarterly carbon intensity values, in gCO2/MJ, for smart charging and electrolysis in 2022.

C Supplementary descriptive statistics

C.1 Triton Charger EV club enrollment survey results

Table C1: Supplementary participant and charging characteristics

A. Demographics							
Affiliation	(1) Staff	(2) Faculty	(3) Undergraduate	(4) Graduate	(5) Other		
	49.13	20.67	17.8	11.45	.95		
Living Arrangement	(1) Own House	(2) Rent off-campus	(3) Own condo	(4) Rent house	(5) On-campus	(6) Other	
	42.61	24.17	10.33	9.7	9.7	9.7	
B. Charging Characteristics							
Charging Location (%)	(1) Campus	(2) Residence	(3) Other	(4) Neighborhood	(5) Destination	(6) Other Home	
	42.58	38.68	7.81	5.24	4.95	.74	
Charging Time (%)	(1) Night	(2) Morning	(3) Afternoon	(4) Evening			
	39.33	26.54	19.33	14.8			
Charging Motivation (%)	(1) Low Prices	(2) Activities	(3) Find Charger	(4) Campus	(5) Parking	(6) Fast Charger	(7) Environment
	35.55	17.21	16.51	11.8	9.52	7.31	2.1
On-campus Charging (%)	(1) Close Office	(2) Open Stall	(3) Long Dwell	(4) Short Time	(5) Environment		
	38.93	30.82	23.82	4.72	1.71		

Notes: The table presents additional summary statistics for demographics (Panel A) and charging characteristics(Panel B) and for experiment participants from the Triton Chargers EV club enrollment survey prior to the experiment.

Table C2: Balance table

	Information		Discount 1		Discount 2	
	Treated	Control	Large	Small	Large-large	Large-small
A.Demographics						
Age	38.58	37.92	38.48	37.79	38.35	38.61
	(13.33)	(12.43)	(12.65)	(13.34)	(12.36)	(12.36)
	[.42]		[.4]		[.04]	
Share male (%)	0.50	0.57	0.58	0.45	0.55	0.61
	(.5)	(.5)	(.49)	(.5)	(.5)	(.5)
	[3.55]		[9.79]		[1.45]	
Income ($ '000)	138.39	133.03	136.69	133.82	137.09	136.28
	(66.21)	(66.97)	(66.94)	(66)	(66.45)	(66.45)
	[.9]		[.23]		[.01]	
Years of education	17.32	17.04	17.40	16.74	17.47	17.33
	(3.14)	(3.04)	(3.06)	(3.11)	(3.17)	(3.17)
	[1.36]		[6.34]		[.21]	
Days on campus per week	3.23	3.29	3.28	3.22	3.28	3.27
	(1.75)	(1.76)	(1.76)	(1.74)	(1.76)	(1.76)
	[.16]		[.13]		[0]	
B.Vehicle attributes						
Vehicle age (years)	2.40	2.37	2.44	2.27	2.50	2.39
	(2.87)	(2.29)	(2.69)	(2.4)	(2.68)	(2.68)
	[.02]		[.67]		[.15]	
Battery electric (%)	0.76	0.77	0.75	0.80	0.79	0.70
	(.43)	(.42)	(.44)	(.4)	(.41)	(.41)
	[.2]		[1.92]		[4.35]	
Odometer reading ('000 miles)	31.56	30.59	31.77	29.79	32.56	30.93
	(31.5)	(27.17)	(28.9)	(30.34)	(27.87)	(27.87)
	[.12]		[.46]		[.23]	
C.Commuting and charging habits						
Daily mileage (miles)	34.27	38.38	36.53	35.93	37.74	35.10
	(27.81)	(30.28)	(26.94)	(32.66)	(29.53)	(29.53)
	[1.79]		[.03]		[.55]	
Home charger (%)	0.59	0.58	0.59	0.58	0.59	0.60
	(.49)	(.49)	(.49)	(.5)	(.49)	(.49)
	[.08]		[.13]		[.01]	
Charging price ($ per kWh)	0.18	0.18	0.18	0.19	0.17	0.19
	(.12)	(.12)	(.12)	(.12)	(.12)	(.12)
	[.35]		[.65]		[1.78]	
Number of Observation	315	314	418	211	210	208

Notes: The table presents the average values and balance tests on driver demographics (Panel A), vehicle attributes (Panel B), commuting and charging habits (Panel C) for treated and control groups of the informational, first and second financial intervention. Robust standard errors are in parentheses. ANOVA p-values from one-way ANOVA tests for differences in means across groups are in backets. Driver data are from the Triton Chargers EV club enrollment survey prior to the experiment. We report averages for age, income, and education, while our survey data asked respondents to select the appropriate bracket for each.

C.2 UCSD EV network operation

To calculate the daily "effective" network utilization that drivers experience on campus, we classify chargers daily as either operational, non-operational, or out-of-service (Figure C1). A charger is "operational" if it reported at least one successful charging session on a given day. A charger is "non-operational" if it recorded glitch sessions (i.e., those that last fewer than five minutes or supply fewer than 0.5 kWh of energy). A charge is "out-of-service" if it reports numerous successive days without activity: for a given day without activity, if either the previous or following day saw a successful session, the charger is operational. If both these days saw only glitches, the charger is non-operational. If the charger does not report activity for ten consecutive days, it is out-of-service.

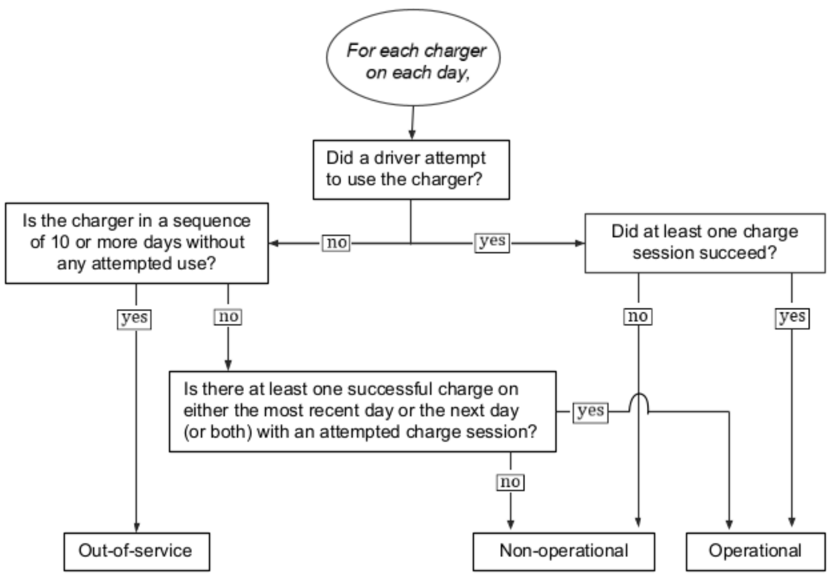


Figure C1: Network operation flowchart

Notes: This figure shows the classification of charger designations into operational, non-operational, and out-of-service.

Figures C2 and C3 report charger designations by day for PowerFlex and ChargePoint, respectively, during the study period (October 4 – November 19). PowerFlex chargers show variability across parking garages. The Athena parking structure rarely has more than one non-operational station and none out-of-service. In contrast, a few charge ports in the Gilman and Hopkins parking structures were mostly non-operational. Similarly for ChargePoint garages, the Gilman chargers show a relatively high non-operational frequency and a larger share of chargers overall reported no charge attempts.

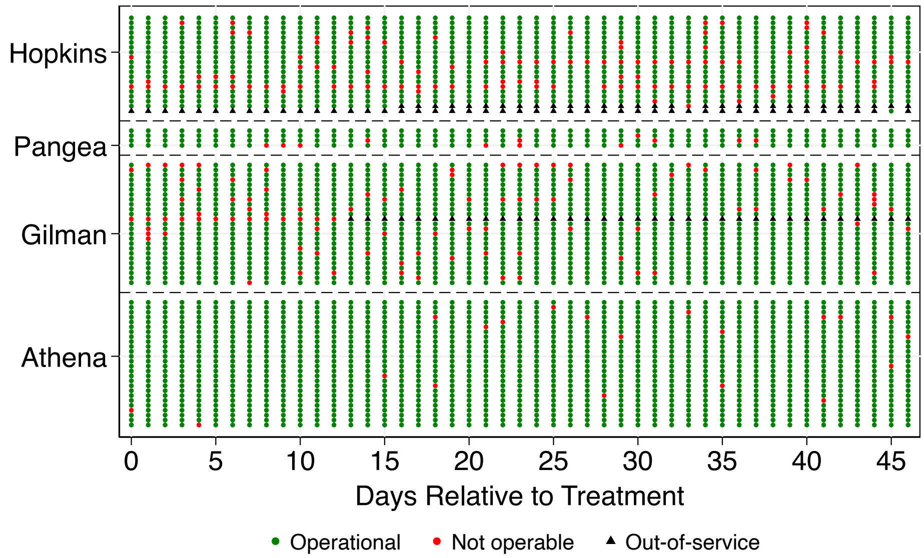


Figure C2: PowerFlex charger designation by day

Notes: This figure shows the daily designation for each PowerFlex charger: operational (green), non-operational (red), and out-of-service (black). Each row is a single charge port over time, while each column is a single day across all chargers. The chargers are grouped by the parking garage.

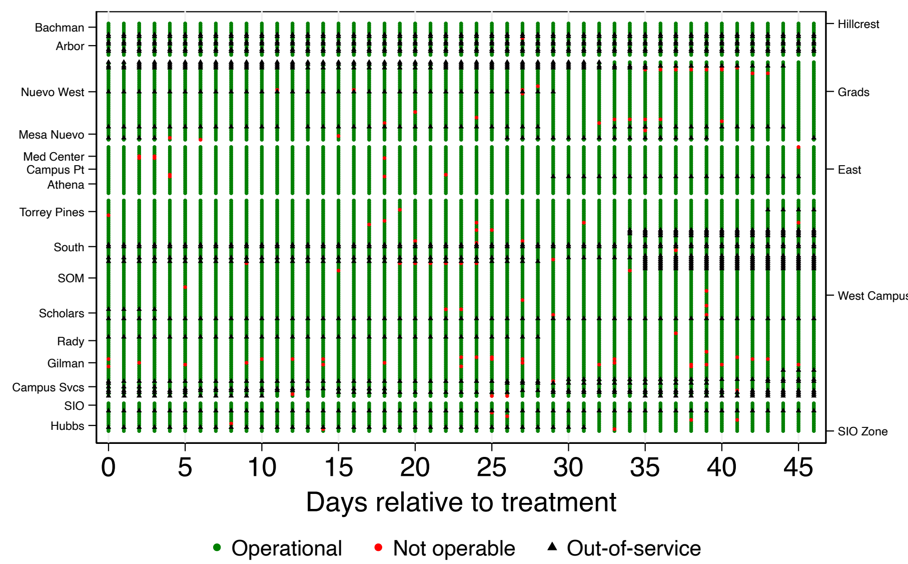


Figure C3: ChargePoint charger designation by day

Notes: This figure shows the daily designation for each ChargePoint charger: operational (green), non-operational (red), and out-of-service (black). Each row is a single charge port over time, while each column is a single day across all chargers. Stations are ordered by garage (on the left y-axis), and garages are ordered by region of campus (on the right y-axis).

Figures C4 report the network-wide share of PowerFlex and ChargePoint chargers that were operational, non-operational, or out-of-service during the study period. For PowerFlex, non-operational and out-of-service chargers compose about 10% and 2% of total chargers; about 90% were thus operational. For ChargePoint, we observe higher out-of-service rate and more moderate non-operational frequency; roughly 86% of ChargePoint ports were operational on any given day. These estimates of network congestion represent a lower bound because they neglect "stall-napping"—occasions when vehicles occupy a charging stall without actually charging yet reduce charger availability all the same.

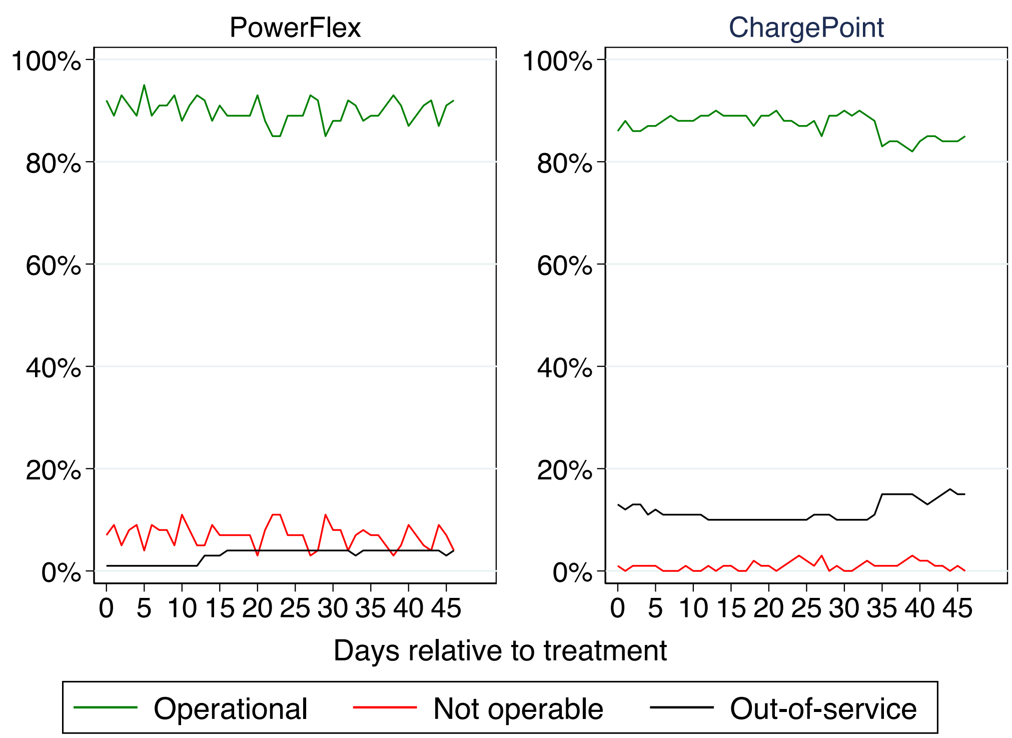


Figure C4: Designation share

Notes: This figure shows the network-wide share of PowerFlex and ChargePoint chargers that were operational (green), non-operational (red), or out-of-service (black) during the study period.

C.3 UCSD EV network utilization

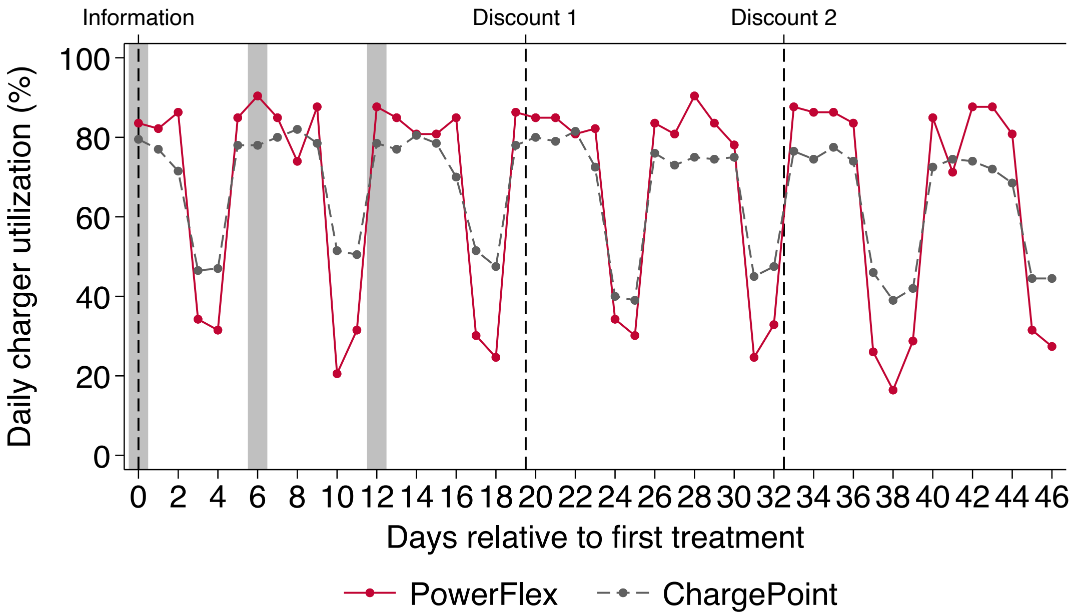


Figure C5: Network utilization by day

Notes: This figure shows charging network utilization for PowerFlex (red) and ChargePoint (blue) chargers by day in the experiment. Day 0 denotes the first day of the informational treatment. We define charger utilization as the percentage of chargers used in a given day relative to all chargers used during the experiment period (October 4 - November 19). 100 indicates that all chargers were used at least once during that day. Vertical dashed lines denote the start of each intervention; thick gray lines denote days on which the informational prompt was sent. We exclude chargers that are non-operational and out-of-service from the network utilization (Section C.2).

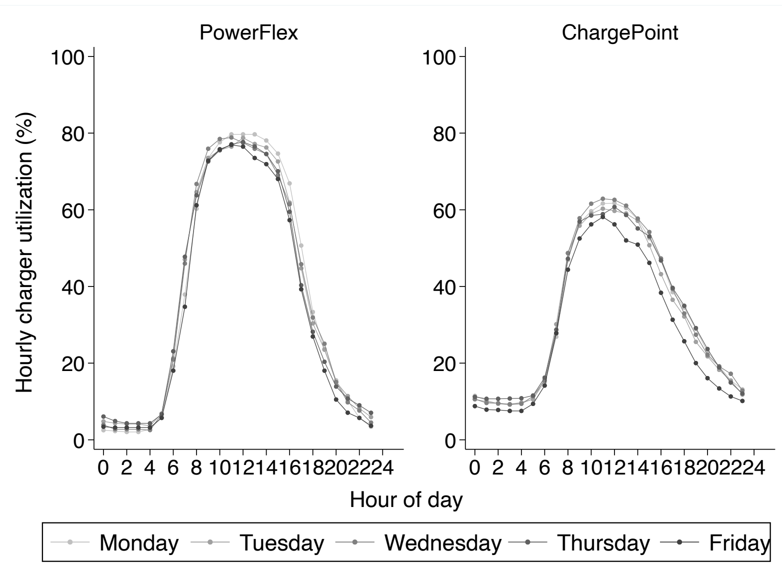


Figure C6: Network utilization by day of the week

Notes: This figure shows hourly utilization of PowerFlex and ChargePoint chargers for different days of the week during the experiment period. We define hourly charger utilization as the percentage of chargers used in a given hour relative to all chargers used during the experiment period.

C.4 Charging sessions glitches

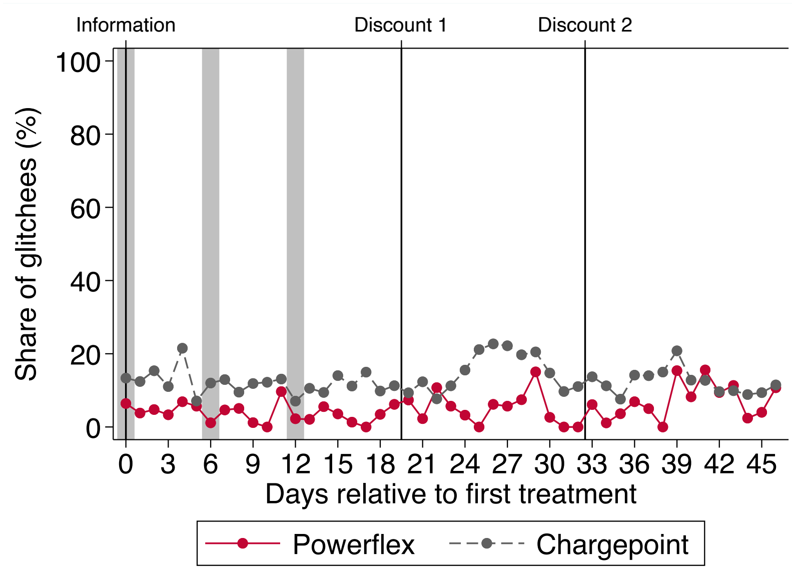


Figure C7: Charging session glitch rate

Notes: The figure displays the percentage of charging sessions experiencing glitches for PowerFlex and ChargePoint chargers by day. Day 0 denotes the first day of the informational treatment. We define a "glitched" session as one that lasts fewer than 5 minutes or consumes less than .5 kWh. Vertical lines denote the start of each intervention; thick gray lines denote days on which the informational prompt was sent.

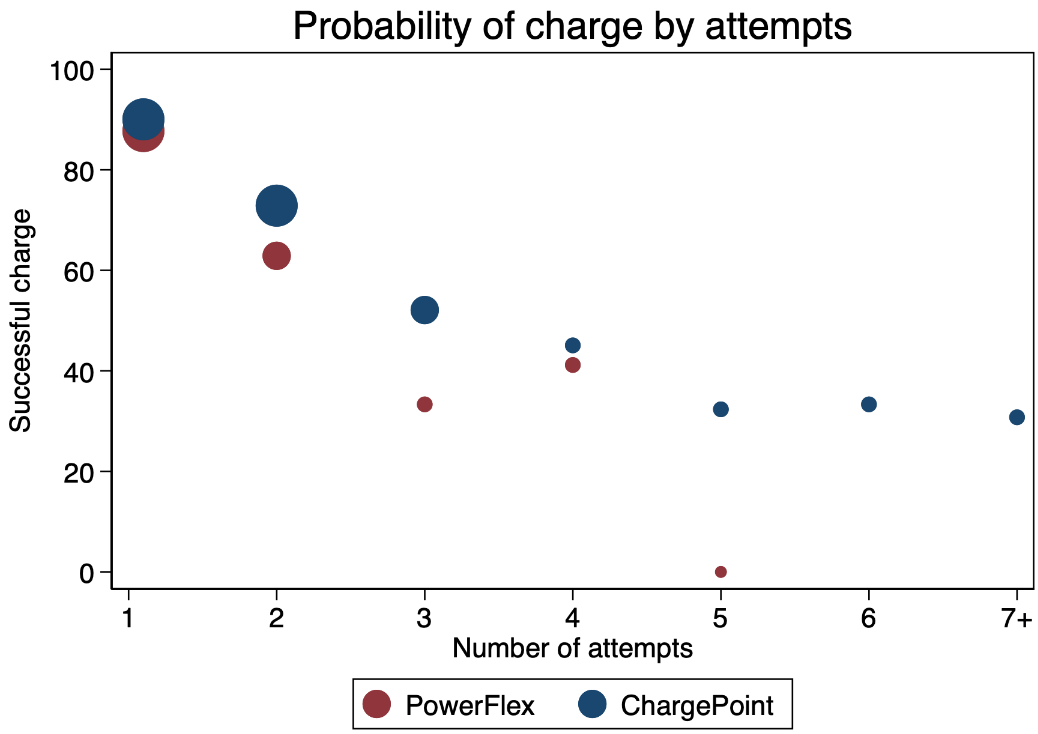
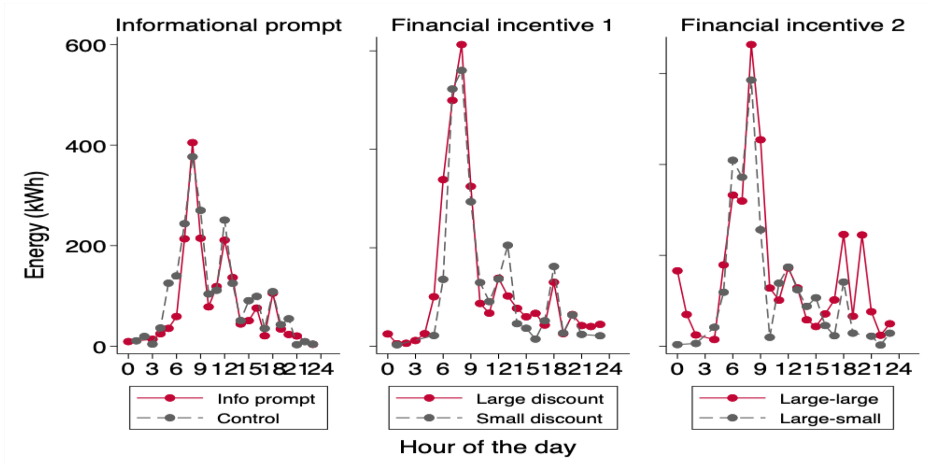


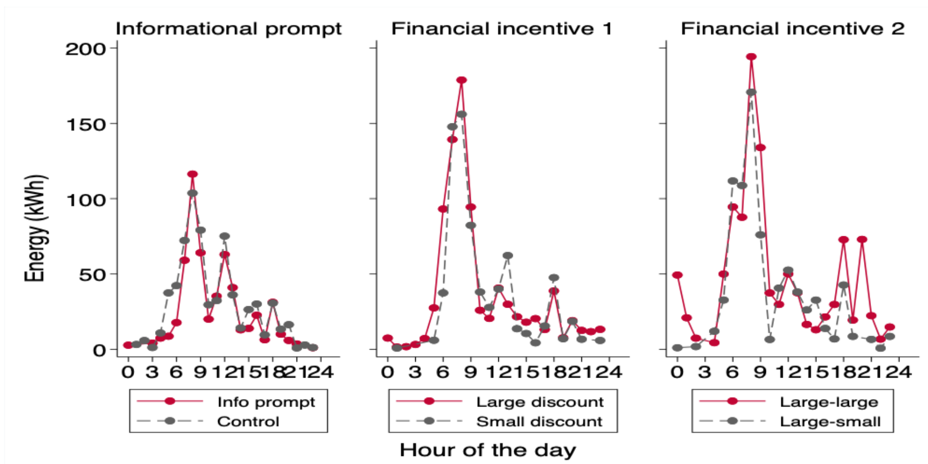
Figure C8: Probability of campus charging by attempts

Notes: This figure shows the effective probability of campus charging by the number of attempts for PowerFlex (red) and ChargePoint (blue). The size of the marker reflects the number of charging sessions, with bins of n=1-10, 11-100, 101-1,000, and 1,000+.

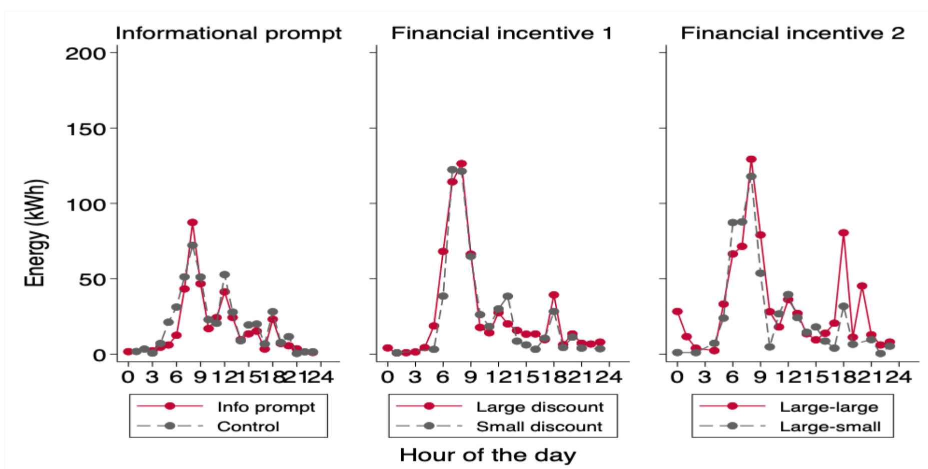
C.5 Timing of charging activities



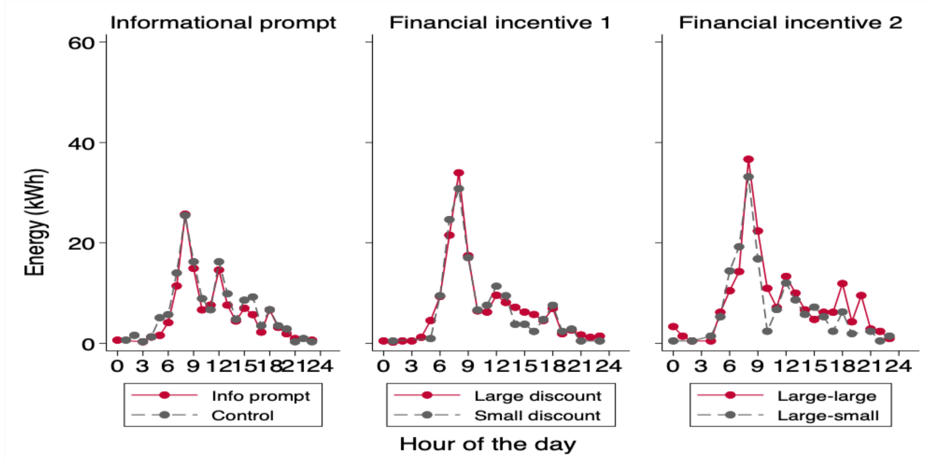
(a) Energy consumed



(b) Session cost



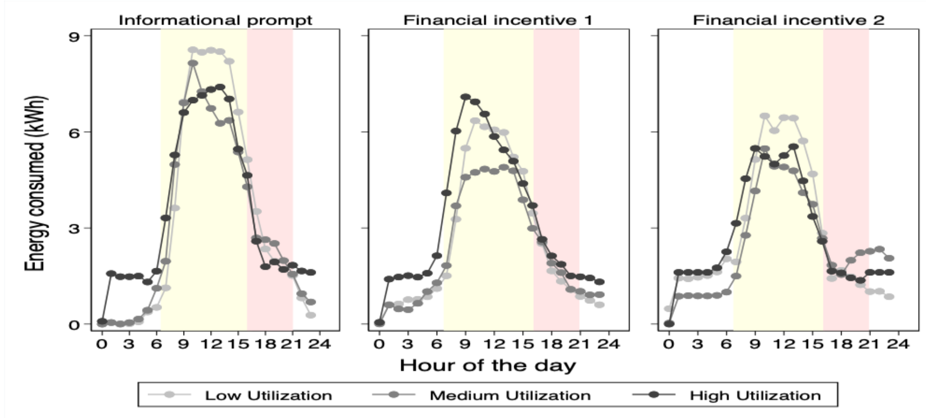
(c) Session duration



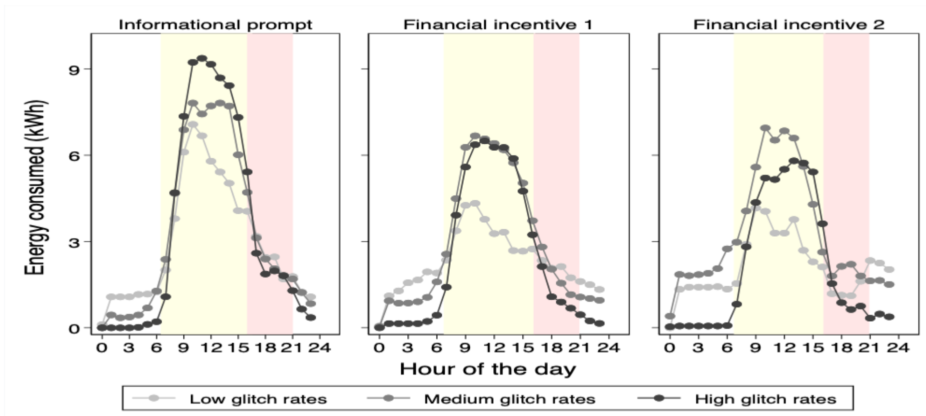
(d) Number of charging sessions

Figure C9: Total charging behavior by hour of the day

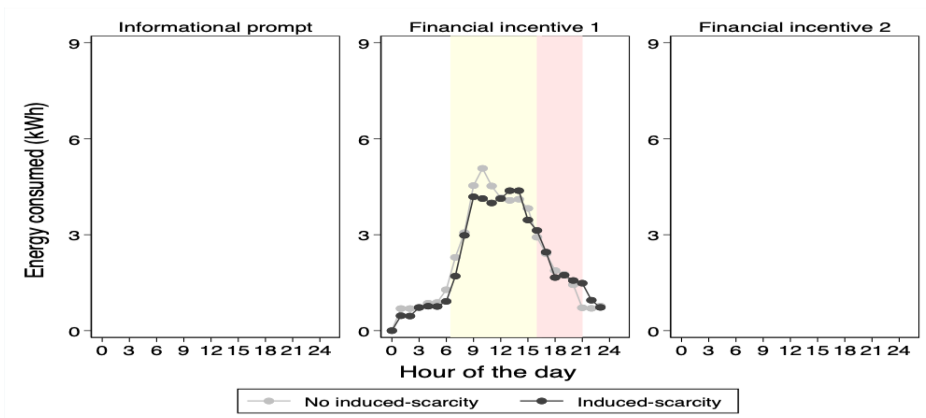
Notes: This figure shows the average charging activities per driver by time of the day. Shown are energy consumed per session (A), session cost (B), session duration (C), and number of charging sessions (D). Data are the average, by hour, of all days in the respective intervention period The three columns of panels (from left to right) show results for the informational intervention, financial intervention (L vs. S discount treatments), and analysis of habit formation (LL vs. LS discount treatments).



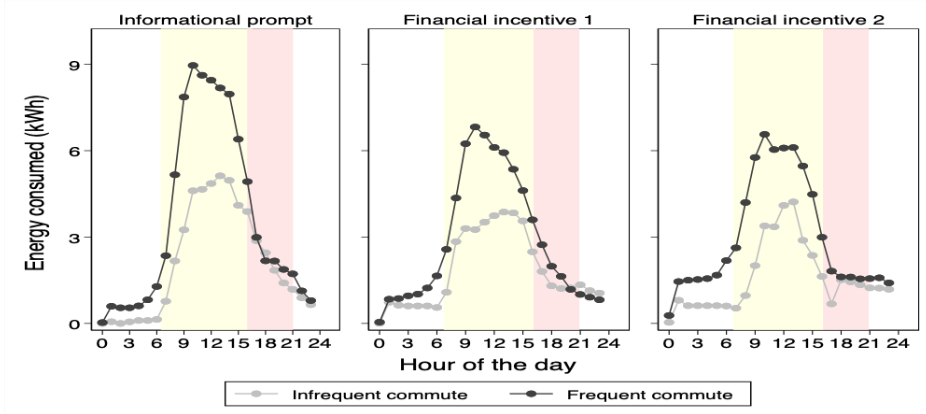
(e) Network utilization



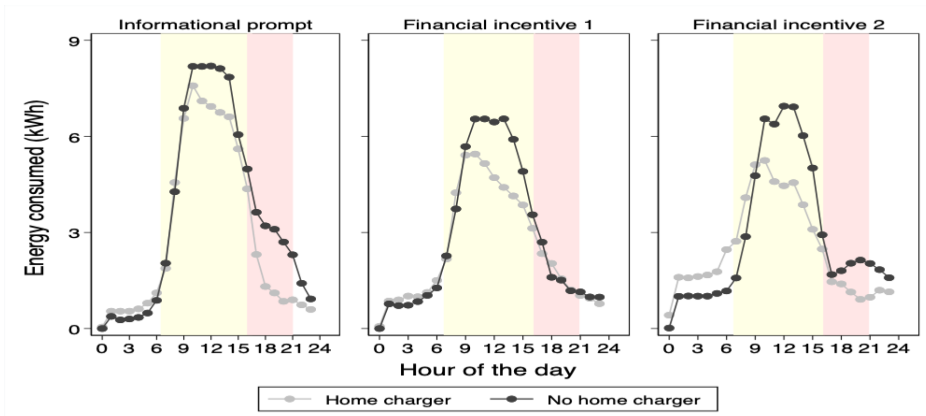
(f) Charger unreliability



(g) Incentive-induced scarcity



(h) Commute frequency



(i) Access to home charger

Figure C10: Energy consumed by hour of the day and mechanisms

Notes: The figure displays the average energy consumed for treated drivers, by hour of the day, over the course of each intervention – the informational (left), first financial (middle), and second financial treatment (right). We show average energy consumed per driver for five mechanisms: Network utilization (Panel a), session glitch rate (Panel b), incentive-induced scarcity (Panel c), commute frequency (Panel d), and access to home charging (Panel e). To calculate total energy delivered, we assume that energy is dispensed to the EV uniformly while actively charging. Light yellow and red bars refer to periods with low and high average carbon intensity of California's power grid.

D Additional regression results

D.1 Effect on average charging behavior

Table D1: Effect on average charging behavior

	Total charging behavior				
	(1) Energy	(2) Cost	(3) Duration	(4) Charge time	(5) Idle time
A. Informational prompt	-.183	-.062	-6.206	-.414	-5.791
	(1.040)	(.287)	(17.037)	(12.695)	(7.848)
Mean Dep. Var.	10.14	2.81	175.52	126.97	48.54
B. Financial incentive 1	1.857*	.537*	22.615	19.425	3.190
	(1.107)	(.320)	(17.533)	(13.264)	(7.184)
Mean Dep. Var.	9.970000000000001	2.88	163.69	122.15	41.54
C. Financial incentive 2	1.367	.359	36.150*	16.148	20.020*
	(1.376)	(.404)	(21.504)	(15.836)	(10.616)
Mean Dep. Var.	10.26	2.98	171.72	121.74	49.97
D. Information x large discount	-.840	-.210	-20.787	-14.905	-5.878
	(1.080)	(.306)	(17.590)	(13.012)	(8.263)
Observation	629	629	629	629	629

Notes: This table presents the regression estimates on the average charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as interaction effects (Panel D). The outcome variables indicate the average energy consumed, in kWh (column 1); average cost, in U.S. dollars (column 2); average session duration, in minutes (column 3); average charging duration (column 4); and average idle duration (column 5). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. The number of observations is reported in the last row. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D.2 Effect on total charging behavior

Table D2: Effect on total charging behavior by charger vendor

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge time	(7) Idle time
A.Informational prompt							
PowerFlex	1.128	.129	1.272	.309	-2.942	16.886	-19.857
	(2.797)	(.163)	(4.011)	(1.010)	(81.577)	(54.072)	(37.582)
ChargePoint	-.620	-.164	-3.416	-1.071	-54.803	-47.187	-7.616
	(3.442)	(.234)	(4.287)	(1.265)	(73.155)	(50.758)	(32.568)
B.Financial incentive 1							
PowerFlex	1.028	.039	3.457	.948	21.827	24.941	-3.117
	(3.121)	(.102)	(2.500)	(.669)	(47.707)	(35.084)	(17.986)
ChargePoint	-1.217	-.061	2.216	.669	33.489	32.271	1.218
	(4.021)	(.177)	(3.354)	(1.006)	(53.330)	(38.325)	(23.516)
C.Financial incentive 2							
PowerFlex	-2.830	.073	.756	.197	17.201	3.067	14.171
	(3.321)	(.128)	(3.094)	(.815)	(58.165)	(36.358)	(28.277)
ChargePoint	3.231	.229	4.248	1.293	65.868	58.990	6.878
	(4.403)	(.222)	(4.931)	(1.484)	(76.596)	(59.859)	(28.305)
D.Interaction							
PowerFlex	-.432	.015	.612	.205	-38.083	-16.896	-21.211
	(2.826)	(.260)	(6.249)	(1.615)	(130.669)	(82.643)	(65.641)
ChargePoint	-2.502	-.103	-.650	-.256	-62.107	-28.283	-33.824
	(3.285)	(.403)	(7.277)	(2.143)	(121.677)	(87.035)	(52.526)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as interaction effects (Panel D) by charger vendor. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D3: Effect on total charging behavior by network utilization

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Low Network Utilization	-1.319	-.229	4.571	1.063	-87.606	-2.212	-85.403
	(7.955)	(.590)	(9.940)	(2.833)	(183.386)	(119.599)	(92.013)
Medium Network Utilization	7.224	1.206**	9.158	2.092	111.227	210.312	-99.126
	(9.142)	(.603)	(10.896)	(2.996)	(202.102)	(156.149)	(90.094)
High Network Utilization	-4.173	-1.309**	-19.919	-5.683*	-277.204	-324.391*	47.097
	(7.912)	(.603)	(12.085)	(3.325)	(264.719)	(172.222)	(140.101)
B.Financial incentive 1							
Low Network Utilization	-5.215	-.797**	3.279	.860	-117.011	-31.206	-85.816
	(7.089)	(.404)	(7.584)	(2.239)	(140.612)	(87.690)	(75.932)
Medium Network Utilization	-5.625	.065	6.663	2.025	-3.249	86.436	-89.627
	(8.308)	(.394)	(7.552)	(2.220)	(131.433)	(98.911)	(57.523)
High Network Utilization	1.948	-.241	9.697	2.872	195.697	96.351	99.301
	(8.695)	(.440)	(9.585)	(2.752)	(196.711)	(136.429)	(97.569)
C.Financial incentive 2							
Low Network Utilization	-5.561	-.065	1.542	.481	-81.509	-76.659	-4.806
	(6.935)	(.471)	(10.184)	(3.006)	(153.182)	(112.541)	(75.547)
Medium Network Utilization	-2.621	1.207**	3.989	1.595	91.244	148.070	-56.747
	(10.083)	(.606)	(9.391)	(2.835)	(180.086)	(125.214)	(89.462)
High Network Utilization	8.096	.343	8.051	2.451	284.576	202.654	81.981
	(9.103)	(.542)	(15.814)	(4.570)	(271.780)	(208.393)	(104.334)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by network utilization. Low network utilization refers to less than 60% of weekday utilization at the most used garage by 9 am, medium network utilization to 60-75%, and high network utilization above 75%. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D4: Effect on total charging behavior by location

	Total charging behavior					
	(1) Sessions	(2) Energy	(3) Cost	(4) Duration	(5) Charge Time	(6) Idle Time
A.Informational prompt						
SIO	.033	.404	.269	9.006	9.185	-.180
	(.069)	(.841)	(.428)	(18.334)	(15.356)	(3.659)
West Campus	.101	.146	-.290	18.412	32.588	-14.177
	(.224)	(4.257)	(1.934)	(119.942)	(87.748)	(50.258)
East Campus	-.003	-1.445	-1.176	-116.159	-90.511	-25.648
	(.151)	(3.622)	(1.847)	(145.214)	(92.523)	(69.111)
Graduate Housing	-.121	-1.600	-.922	-76.622	-32.538	-44.085
	(.101)	(2.390)	(1.360)	(74.342)	(48.680)	(30.843)
B.Financial incentive 1						
SIO	-.142**	-2.246**	-1.152*	-46.530*	-37.130*	-9.400
	(.069)	(1.081)	(.664)	(27.121)	(22.448)	(6.232)
West Campus	-.043	2.083	.378	-73.509	-27.367	-46.141
	(.171)	(3.148)	(1.734)	(110.968)	(80.432)	(49.228)
East Campus	.125	4.167*	1.910	75.593	82.619	-7.026
	(.084)	(2.252)	(1.390)	(95.253)	(65.957)	(42.431)
Graduate Housing	-.046	.128	.010	-16.046	-8.585	-7.462
	(.082)	(2.088)	(1.366)	(61.909)	(47.246)	(23.170)
C.Financial incentive 2						
SIO	.016	.217	.017	1.032	.383	.649
	(.026)	(.493)	(.300)	(12.238)	(10.143)	(3.701)
West Campus	.038	-.561	-1.262	-102.791	-47.679	-55.113
	(.223)	(3.545)	(1.893)	(111.924)	(75.846)	(56.258)
East Campus	.065	1.903	.314	-9.775	22.534	-32.309
	(.108)	(2.967)	(1.581)	(122.744)	(81.660)	(57.001)
Graduate Housing	.144	3.996	1.627	76.625	44.860	31.764*
	(.088)	(3.361)	(1.629)	(64.308)	(54.802)	(18.853)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by vehicle type. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D5: Effect on total charging behavior by glitch rate

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Low Glitch Rate	-16.232	-.882	-11.418	-2.953	-347.024	-170.931	-176.073
	(10.445)	(.736)	(13.085)	(3.668)	(251.577)	(172.206)	(126.466)
Medium Glitch Rate	.886	-.293	-7.865	-2.333	-163.103	-154.478	-8.693
	(5.977)	(.457)	(7.873)	(2.255)	(156.081)	(100.775)	(84.122)
High Glitch Rate	14.316	1.114	27.719*	6.599	399.831	442.235*	-42.438
	(11.025)	(.832)	(16.774)	(4.501)	(294.593)	(230.931)	(116.585)
B.Financial incentive 1							
Low Glitch Rate	-9.222	-.555	-.031	.161	-94.038	-2.828	-91.204
	(9.971)	(.474)	(8.555)	(2.516)	(179.482)	(108.936)	(102.898)
Medium Glitch Rate	.069	-.293	7.658	2.224	31.908	44.220	-12.313
	(6.377)	(.319)	(6.997)	(2.040)	(121.077)	(86.695)	(55.666)
High Glitch Rate	-6.471	-.527	6.894	1.780	-3.794	60.024	-63.812
	(10.552)	(.645)	(11.125)	(3.208)	(200.953)	(160.479)	(80.958)
C.Financial incentive 2							
Low Glitch Rate	-2.927	.891*	3.525	1.112	-58.957	42.950	-101.868
	(9.295)	(.485)	(13.452)	(3.931)	(225.931)	(152.935)	(103.593)
Medium Glitch Rate	1.268	.566	6.578	2.221	119.085	106.236	12.869
	(7.310)	(.465)	(9.944)	(2.909)	(164.604)	(127.049)	(68.893)
High Glitch Rate	-7.943	-.612	-1.804	-.433	-34.588	-86.109	51.679
	(10.853)	(.528)	(11.243)	(3.298)	(215.403)	(145.771)	(116.189)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by vehicle type. Low glitch rates refer to less than 10% of weekday charging sessions experienced a glitch at the most used garage by 9 am, medium glitch rates to 10-20%, and high network utilization above 25%. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D6: Effect on total charging behavior by scarcity

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge time	(7) Idle time
A. Induced scarcity	-4.286	.082	-1.598	-.520	-23.370	-1.639	-21.747
	(4.344)	(.200)	(3.997)	(1.181)	(69.087)	(49.522)	(30.672)
B. Financial incentive	-1.646	.149	2.690	.873	25.872	4.484	21.387
	(4.371)	(.197)	(4.046)	(1.208)	(67.659)	(49.240)	(30.047)
C. Scarcity x large discount	-5.010	.095	1.295	.469	-15.341	8.907	-24.267
	(4.578)	(.229)	(4.495)	(1.347)	(74.647)	(53.125)	(31.589)
Mean Dep. Var.	30.61	1.57	28.67	8.529999999999999	508.93	365.66	143.26
Observation	313	629	629	629	629	629	629

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by network utilization. Low network utilization refers to less than 60% of weekday utilization at the most used garage by 9 am, medium network utilization to 60-75%, and high network utilization above 75%. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D7: Effect on total charging behavior by commute frequency

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Infrequent Commute	-5.847	.021	-5.316	-1.459	-180.663	-76.156	-104.519**
	(6.256)	(.362)	(6.834)	(1.892)	(121.883)	(85.478)	(52.442)
Frequent Commute	2.679	-.013	.367	-.172	16.773	8.397	8.345
	(4.778)	(.339)	(6.637)	(1.840)	(125.149)	(84.545)	(60.067)
B.Financial incentive 1							
Infrequent Commute	-1.536	-.147	-2.875	-.916	-94.435	-55.247	-39.174
	(6.032)	(.247)	(5.234)	(1.513)	(87.589)	(64.274)	(35.244)
Frequent Commute	-1.899	.016	9.624*	2.826*	119.536	109.884	9.649
	(5.499)	(.251)	(5.112)	(1.494)	(90.478)	(67.347)	(37.833)
C.Financial incentive 2							
Infrequent Commute	-16.281**	-.061	-7.989	-2.378	-43.946	-77.764	33.823
	(6.684)	(.326)	(6.310)	(1.880)	(101.390)	(74.869)	(42.588)
Frequent Commute	6.269	.494	11.495	3.438	153.660	130.831	22.877
	(6.168)	(.307)	(7.787)	(2.279)	(124.054)	(92.348)	(52.162)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by commute distance. An infrequent commuter comes to the campus less than three times; a frequent commuter more than three times. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D8: Effect on total charging behavior by home charging access

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Home Charger	1.956	-.198	-7.118	-2.275	-107.906	-51.950	-55.960
	(4.667)	(.341)	(6.800)	(1.871)	(133.845)	(84.035)	(69.192)
No Home Charger	-4.151	.295	7.092	1.968	45.146	31.091	13.999
	(7.721)	(.464)	(8.830)	(2.468)	(154.945)	(118.734)	(58.587)
B.Financial incentive 1							
Home Charger	-.399	-.007	6.250	1.752	9.996	49.083	-39.090
	(5.054)	(.236)	(4.666)	(1.353)	(88.086)	(57.728)	(43.799)
No Home Charger	-4.091	-.084	4.095	1.260	96.917	59.406	37.520
	(7.585)	(.361)	(6.702)	(1.946)	(114.641)	(88.730)	(42.706)
C.Financial incentive 2							
Home Charger	-.834	.145	4.448	1.444	47.175	51.465	-4.263
	(5.885)	(.272)	(7.303)	(2.136)	(112.531)	(80.926)	(48.251)
No Home Charger	-2.224	.558	6.118	1.671	150.305	78.997	71.353
	(8.828)	(.420)	(8.121)	(2.386)	(138.505)	(106.828)	(57.916)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) depending on whether participants have access to home charging. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D9: Effect on total charging behavior by typical charging rate paid

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Low Charge Rate	-1.767	-.497	-2.632	-1.028	-94.538	-69.036	-25.529
	(6.309)	(.346)	(8.138)	(2.351)	(138.086)	(95.185)	(64.812)
Medium Charge Rate	-1.465	.061	-1.832	-.500	-52.166	-15.059	-37.138
	(4.591)	(.327)	(6.164)	(1.709)	(117.655)	(82.983)	(55.433)
High Charge Rate	5.268	.309	.651	-.405	13.119	19.204	-6.090
	(8.232)	(.531)	(10.150)	(2.748)	(186.210)	(126.359)	(82.244)
B.Financial incentive 1							
Low Charge Rate	-.894	-.659**	-6.832	-2.161	-123.415	-85.363	-38.061
	(7.030)	(.289)	(5.341)	(1.538)	(101.065)	(67.041)	(51.567)
Medium Charge Rate	-1.561	.079	6.691	1.989	88.394	77.999	10.394
	(5.025)	(.222)	(4.402)	(1.279)	(80.054)	(57.696)	(35.577)
High Charge Rate	-3.759	.267	14.667*	4.269*	98.930	128.741	-29.784
	(8.719)	(.375)	(8.158)	(2.355)	(139.484)	(98.702)	(53.167)
C.Financial incentive 2							
Low Charge Rate	-9.458	-.127	-7.040	-2.211	-49.365	-85.670	36.320
	(6.309)	(.276)	(5.732)	(1.618)	(108.299)	(68.658)	(55.742)
Medium Charge Rate	-4.251	.405	5.868	1.815	98.804	83.384	15.447
	(5.475)	(.329)	(7.242)	(2.145)	(111.691)	(88.551)	(44.720)
High Charge Rate	3.282	.552	17.529	5.195	226.021	176.331	49.769
	(9.140)	(.478)	(13.362)	(3.896)	(231.265)	(154.578)	(92.654)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by the typical rate that participants pay for EV charging. Low rates are those <$.17/kWh; medium rates, <$.17/kWh and >$.23/kWh; and high rates, >$.23/kWh. The outcome variables indicate the share of campus charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session cost, in U.S. dollars (column 4); session duration, in minutes (column 5); charging duration (column 6); and idle duration (column 7). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D10: Effect on total weekend charging behavior

	Total charging behavior					
	(1) Sessions	(2) Energy	(3) Cost	(4) Duration	(5) Charge time	(6) Idle time
A. Informational prompt	-.053	.119	.237	-32.770	1.662	-34.432
	(.063)	(1.531)	(.878)	(50.028)	(36.658)	(21.296)
Mean Dep. Var.	.31	5.44	2.96	173.02	125.21	47.82
B. Financial incentive 1	.018	1.347	1.400*	66.154	44.172	21.982
	(.064)	(1.337)	(.787)	(46.419)	(31.138)	(21.902)
Mean Dep. Var.	.25	4.74	2.82	159.2	113.05	46.15
C. Financial incentive 2	.080	1.307	.069	-13.209	-4.160	-9.049
	(.078)	(2.172)	(1.177)	(60.909)	(45.273)	(22.734)
Mean Dep. Var.	.27	5.31	3.07	164.43	122.16	42.27
D. Information x large discount	-.047	.372	1.027	5.720	24.249	-18.529
	(.113)	(2.584)	(1.386)	(76.159)	(58.637)	(29.083)
Observation	629	629	375	375	375	375

Notes: This table presents the regression estimates on weekeend charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as interaction effects (Panel D). The outcome variables indicate the number of charging sessions (column 1); total energy consumed, in kWh (column 2); session cost, in U.S. dollars (column 3); session duration, in minutes (column 4); charging duration, in minutes (column 5); and idle duration, in minutes (column 6) during the weekend. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. The number of observations is reported in the last row. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D.3 Effect on the timing of charging behavior

Table D11: Effect on the timing of charging by utilization

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Low Network Utilization	-.273*	-.191	.634*	-.163	-.235
	(.162)	(.155)	(.338)	(.366)	(.189)
Medium Network Utilization	.120	-.189	.756*	.168	.353
	(.103)	(.193)	(.447)	(.302)	(.217)
High Network Utilization	.022	-.165	-.723	-.468	.026
	(.099)	(.228)	(.462)	(.353)	(.257)
B.Financial incentive 1					
Low Network Utilization	.067	.078	-.073	-.435*	-.434***
	(.074)	(.084)	(.248)	(.225)	(.152)
Medium Network Utilization	.225**	-.004	-.290	.078	.055
	(.096)	(.091)	(.281)	(.234)	(.147)
High Network Utilization	.094	.258*	-.664*	-.062	.132
	(.071)	(.153)	(.337)	(.229)	(.185)
C.Financial incentive 2					
Low Network Utilization	.033	-.063	-.228	.068	.181
	(.135)	(.122)	(.264)	(.275)	(.167)
Medium Network Utilization	.111	-.347**	.316	.870**	.580**
	(.134)	(.167)	(.382)	(.360)	(.287)
High Network Utilization	.004	-.092	-.254	.114	.493*
	(.082)	(.281)	(.276)	(.285)	(.285)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by vehicle type. Low network utilization refers to less than 60% of weekday utilization at the most used garage by 9 am, medium network utilization to 60-75%, and high network utilization above 75%. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. The treatment period consists of three phases: informational (Oct 4-23), first financial (Oct 24-Nov 5), and second financial treatment (Nov 6-19). Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D12: Effect on the timing of charging by location

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Sio	.029	.070	-.142	.080	.047
	(.029)	(.074)	(.143)	(.082)	(.041)
West Campus	-.351	-.396	1.185	.250	-.223
	(.251)	(.304)	(1.067)	(.442)	(.289)
East Campus	-.116	-1.020	.134	.091	.342
	(.149)	(.757)	(.997)	(.233)	(.533)
Graduate Housing	-.087	-.266	.110	-.420	-.140
	(.065)	(.332)	(.218)	(.548)	(.135)
B.Financial incentive 1					
Sio	.000	-.066	-.364	-.096	-.063
	(.)	(.064)	(.225)	(.073)	(.058)
West Campus	.042	-.163	-.116	.106	-.043
	(.182)	(.283)	(.854)	(.305)	(.226)
East Campus	.109*	.939***	.135	.047	.012
	(.059)	(.361)	(.486)	(.142)	(.325)
Graduate Housing	.245	.000	.128	-.448	.028
	(.210)	(.)	(.249)	(.335)	(.073)
C.Financial incentive 2					
Sio	.000	.002	.057	.023	.000
	(.)	(.014)	(.105)	(.069)	(.)
West Campus	.158	-.255	-.546	.186	.441
	(.163)	(.363)	(.927)	(.467)	(.325)
East Campus	.000	.046	-.199	.143	.751*
	(.)	(.743)	(.547)	(.131)	(.453)
Graduate Housing	.337	.155	.294	.026	.284*
	(.520)	(.115)	(.311)	(.198)	(.171)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by vehicle type. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. The treatment period consists of three phases: informational (Oct 4-23), first financial (Oct 24-Nov 5), and second financial treatment (Nov 6-19). Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D13: Effect on the timing of charging by glitch rate

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Low Glitch Rate	-.173	-.331*	-.180	-.107	-.091
	(.205)	(.189)	(.488)	(.386)	(.310)
Medium Glitch Rate	-.098	-.087	.099	-.228	.020
	(.099)	(.156)	(.305)	(.275)	(.161)
High Glitch Rate	.067	-.287	1.269**	-.029	.094
	(.155)	(.184)	(.610)	(.366)	(.256)
B.Financial incentive 1					
Low Glitch Rate	.288***	.023	-.541*	-.271	-.055
	(.104)	(.145)	(.309)	(.267)	(.187)
Medium Glitch Rate	.120*	.152*	-.304	-.176	-.084
	(.062)	(.089)	(.227)	(.178)	(.117)
High Glitch Rate	-.045	.030	.027	-.145	-.394
	(.104)	(.135)	(.401)	(.257)	(.276)
C.Financial incentive 2					
Low Glitch Rate	.020	-.255	-.133	.672**	.575**
	(.094)	(.223)	(.355)	(.334)	(.265)
Medium Glitch Rate	.119	-.118	-.178	.418	.514**
	(.120)	(.156)	(.236)	(.261)	(.213)
High Glitch Rate	-.077	-.145	.137	-.189	-.266
	(.116)	(.176)	(.422)	(.341)	(.208)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by vehicle type. Low glitch rates refer to less than 10% of weekday charging sessions experienced a glitch at the most used garage by 9 am, medium glitch rates to 10-20%, and high network utilization above 25%. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. The treatment period consists of three phases: informational (Oct 4-23), first financial (Oct 24-Nov 5), and second financial treatment (Nov 6-19). Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D14: Effect on the timing of charging by charger vendor

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
PowerFlex	-.018	-.051	.151	.045	.035
	(.015)	(.055)	(.137)	(.035)	(.030)
ChargePoint	-.030	-.073	.052	-.094	-.018
	(.043)	(.064)	(.121)	(.130)	(.078)
B.Financial incentive 1					
PowerFlex	-.001	.036	-.023	.008	.003
	(.013)	(.036)	(.092)	(.021)	(.018)
ChargePoint	.062**	.028	-.053	-.051	-.049
	(.028)	(.036)	(.101)	(.088)	(.059)
C.Financial incentive 2					
PowerFlex	.008	-.052	.055	.023	.036
	(.010)	(.062)	(.091)	(.030)	(.032)
ChargePoint	.032	-.009	-.057	.171	.169*
	(.061)	(.054)	(.112)	(.125)	(.089)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by charger vendor. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D15: Effect on the timing of charging by scarcity

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A. Induced scarcity	.064	-.058	-.064	.049	.090
	(.044)	(.058)	(.124)	(.093)	(.063)
B. Financial incentive	.076*	.036	-.010	.026	.021
	(.040)	(.062)	(.117)	(.092)	(.067)
C. Scarcity x large discount	.118*	-.015	-.117	.054	.054
	(.065)	(.070)	(.126)	(.110)	(.068)
Mean Dep. Var.	.07	.15	.6900000000000001	.42	.24
Observation	629	629	629	629	629

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by vehicle type. Low network utilization refers to less than 60% of weekday utilization at the most used garage by 9 am, medium network utilization to 60-75%, and high network utilization above 75%. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. The treatment period consists of three phases: informational (Oct 4-23), first financial (Oct 24-Nov 5), and second financial treatment (Nov 6-19). Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D16: Effect on the timing of charging by commute frequency

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Infrequent Commute	.009	-.073	-.097	.154	.027
	(.073)	(.081)	(.200)	(.175)	(.127)
Frequent Commute	-.076	-.148	.345	-.146	.012
	(.065)	(.098)	(.219)	(.176)	(.108)
B.Financial incentive 1					
Infrequent Commute	.002	-.017	-.105	.088	-.115
	(.044)	(.050)	(.155)	(.125)	(.077)
Frequent Commute	.092**	.106	-.061	-.111	-.009
	(.038)	(.066)	(.161)	(.116)	(.085)
C.Financial incentive 2					
Infrequent Commute	-.084	-.090	.055	.179	-.018
	(.078)	(.078)	(.171)	(.159)	(.138)
Frequent Commute	.100	-.047	-.030	.202	.313***
	(.092)	(.106)	(.170)	(.166)	(.113)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by commute distance. An infrequent commuter comes to the campus less than three times; a frequent commuter more than three times. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D17: Effect on the timing of charging by home charging access

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Home Charger	-.094	-.126	.155	-.081	-.051
	(.076)	(.112)	(.235)	(.171)	(.090)
No Home Charger	.022	-.120	.274	-.000	.120
	(.060)	(.104)	(.264)	(.225)	(.178)
B.Financial incentive 1					
Home Charger	.044	.065	-.045	.004	-.076
	(.045)	(.069)	(.161)	(.120)	(.070)
No Home Charger	.086*	.062	-.120	-.108	-.004
	(.045)	(.068)	(.208)	(.159)	(.135)
C.Financial incentive 1					
Home Charger	.073	-.017	-.055	.094	.076
	(.095)	(.103)	(.160)	(.134)	(.082)
No Home Charger	-.010	-.125	.076	.342	.394**
	(.062)	(.101)	(.215)	(.238)	(.184)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) depending on whether participants have access to home charging. The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D18: Effect on the timing of charging by typical charging rate paid

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Low Charge Rate	-.073	-.035	-.242	.054	-.200*
	(.063)	(.109)	(.218)	(.208)	(.117)
Medium Charge Rate	-.063	-.085	.248	-.035	-.004
	(.053)	(.096)	(.221)	(.168)	(.091)
High Charge Rate	.017	-.317**	.511	-.189	.287
	(.075)	(.134)	(.319)	(.243)	(.201)
B.Financial incentive 1					
Low Charge Rate	-.022	.050	-.294	-.220*	-.172*
	(.034)	(.074)	(.209)	(.114)	(.092)
Medium Charge Rate	.043	.061	-.016	.021	-.030
	(.038)	(.055)	(.143)	(.110)	(.074)
High Charge Rate	.216**	.088	-.029	-.054	.046
	(.090)	(.137)	(.217)	(.162)	(.122)
C.Financial incentive 2					
Low Charge Rate	-.045	-.047	-.102	.054	.001
	(.046)	(.118)	(.176)	(.164)	(.076)
Medium Charge Rate	.083	-.091	.003	.311*	.200
	(.097)	(.081)	(.168)	(.176)	(.131)
High Charge Rate	.002	.017	.104	-.011	.469**
	(.064)	(.232)	(.273)	(.197)	(.229)

Notes: This table presents the regression estimates on the timing of charging for the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by the typical rate that participants pay for EV charging. Low rates are those <\$.17/kWh; medium rates, <\$.17/kWh and >\$.23/kWh; and high rates, >\$.23/kWh.The outcome variables indicate the number of charging sessions during five distinct periods: overnight (21:00 - 4:59) (column 1), early morning (5:00 - 6:59) (column 2), morning (7:00 - 9:59) (column 3), midday (10:00 - 15:59) (column 4), and evening (16:00 - 20:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and vehicle-fixed effects. The mean outcome variable is reported below the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

References

Agency, E. P. (2022). *Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances.*