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

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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 daylight 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, whereas receiving larger financial incentives to charge on campus prompted a shift from daytime to overnight and early morning charging. We identify high network utilization as a possible mechanism that causes increased competition for chargers and earlier arrival times during the financial discount period. The results show substantial heterogeneity among subgroups in temporal shifts, with those having high flexibility to change daily schedules (e.g., students, residents) primarily shifting the timing of their charging. Our findings highlight the importance of informational nudges, network capacity, and driver demographics for crafting sustainable charging policies.

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I Introduction

Every credible plan for deep reductions in greenhouse gas emissions that cause climate change involves the widespread electrification of light-duty transportation (Larson et al., 2021; 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. (Shen et al., 2023), sales are increasing quickly (Gillingham et al., 2023), and major jurisdictions like the E.U., U.S., and California 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). Most visions for deep decarbonization combine a rapid uptake of renewable energy in the power sector alongside a shift to EVs (International Energy Agency, 2021), which could be an enormous demand response resource, i.e., flexible price-responsive load (Muratori & Mai, 2020). However, the success of these plans depends on how drivers charge their vehicles since charging impacts both the power grid, which must meet new demand (Powell et al., 2022), and emissions (Zhang & Fujimori, 2020) since renewable grids have varying marginal emissions throughout the day (Holland et al., 2022). In solar-dominant grids, for instance, that variation puts a premium on midday charging when most people are at work (Arvesen et al., 2021).

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 (Chakraborty et al., 2019). Second, as the electric grid moves toward renewable energy, the value of storage or flexible load options (like EV charging) will grow alongside the need to balance fluctuations in energy supply and demand. (Coignard et al., 2018). With many institutions, including corporations, public entities, and universities, committing to net-zero carbon goals and supporting their employees with workplace charging facilities, the impact of the shift to EVs will depend on how drivers interact with workplace EV networks and how workplace policies affect 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., shift from off-campus to campus charging) and adjust 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 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 some drivers on the large discount while moving others to the small discount to investigate habit formation for campus charging.

Four main empirical findings emerge from our study. First, with one exception, prompts 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. The one exception was the second financial discount that significantly increased the number of campus sessions. These results suggest that informational prompts and financial discounts did not induce a short-term shift to campus charging, and that drivers require time to adjust their behaviors in response to new, lower prices. Because most non-campus charging is done at home overnight, these results further suggest that prompts and discounts did not induce shifts from home to workplace charging. Perceptions of charger scarcity and unreliability may deter drivers from making short-term shifts to campus charging.

Second, although 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 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 charging. Conversely, discounts on campus charging led to a 103% increase in overnight charging and a 61% increase in early morning charging, while

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

charging decreased during the rest of the day. This indicates an intertemporal substitution in the opposite direction, away from midday solar energy generation, suggesting a potentially perverse effect in which financial incentives for charging increase CO_2 emissions. Concerns about scarcity may be causing this shift to earlier charging, as morning commuters arrive earlier to guarantee access to a charger, while campus and local residents, who have greater flexibility in their schedules, shift to overnight sessions when most chargers are unoccupied.[2] The shift to earlier arrival times as a response to financial discounts may be influenced by the high campus EV network utilization rates of around 50–85% during weekdays in the study period. Within congested networks, discounts may instill the belief that drivers need to arrive earlier to campus to secure an available charger and secure the discounts.

Third, the second financial discount resulted in a 88% increase in evening sessions but less of a shift to early morning charging. 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 shift to evening charging may indicate that commuters adapted their routines to charge during periods with higher availability of chargers. Given an average of .89 weekly campus charging sessions per driver, incentives shifted the timing of 15–26% of all charging sessions.

Fourth, we find substantial heterogeneity in how certain groups of drivers respond to the informational prompt and financial incentives, pointing to potential sources of flexibility in EV charging. Drivers with short or frequent commutes and students tend to respond most to information; these groups are likely to have more flexible schedules. Conversely, drivers who may have less flexibility — long-distance commuters, staff (who work more traditional hours), and individuals without home chargers who rely on campus charging — were more likely to shift charging to the early morning period. Drivers with traditional or inflexible schedules who are concerned about scarcity might arrive earlier at the workplace to secure a charger. Those with low environmental motivation also shifted to early morning. Separately, during the second discount, students (some live on campus and may be more price-sensitive) increased charging overnight when the campus EV network has consistently low utilization.

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

[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).

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 home-ownership (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 who 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 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

[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).

(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). Yet, 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 heterogeneity, 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). 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.[5] The financial intervention consists of two phases.[6] During the first phase (October 24 to November 5; 13 days), roughly 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

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

[5]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.

[6]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)

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).

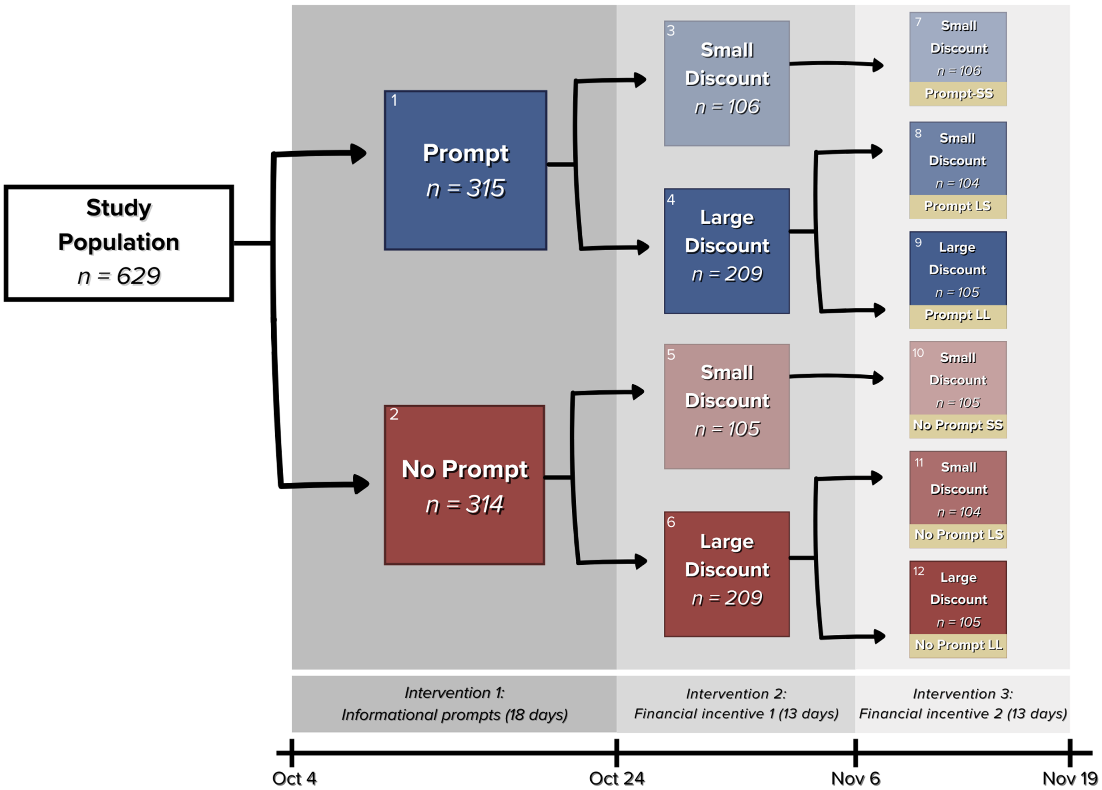


Figure I: Experimental design

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.[7] 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. 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 1 kWh or last fewer than 10 -minutes) or flout campus parking rules (i.e., exceed 16 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.

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

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),[8], 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. Figure C1 shows that participants are mostly staff (49%) and faculty (24%), predominantly white (49%) and Asian (36%), and single-family house owners (44%)[9]. 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, $\$.18/kWh$.[10]

Per vendor session data, drivers initiated .89 weekly charging sessions 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. Par-

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

[9] 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.

[10] 190 participants (30% of the sample) report not knowing the price they typically pay to charge.

ticipants did 30% of their charging on campus (on an energy basis).

Moreover, Figure 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, 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):

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

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;[11] η_t is a dummy variable for UCSD's "Clean Air Day" (Wednesday, October 4), a promotional event with 50% discounts on campus charging;[12] 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 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 $Reward_{2i}$

[11]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.

[12]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; 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.

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.[13]

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.

III.B Main findings

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

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[14] (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

[13] 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).

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

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.

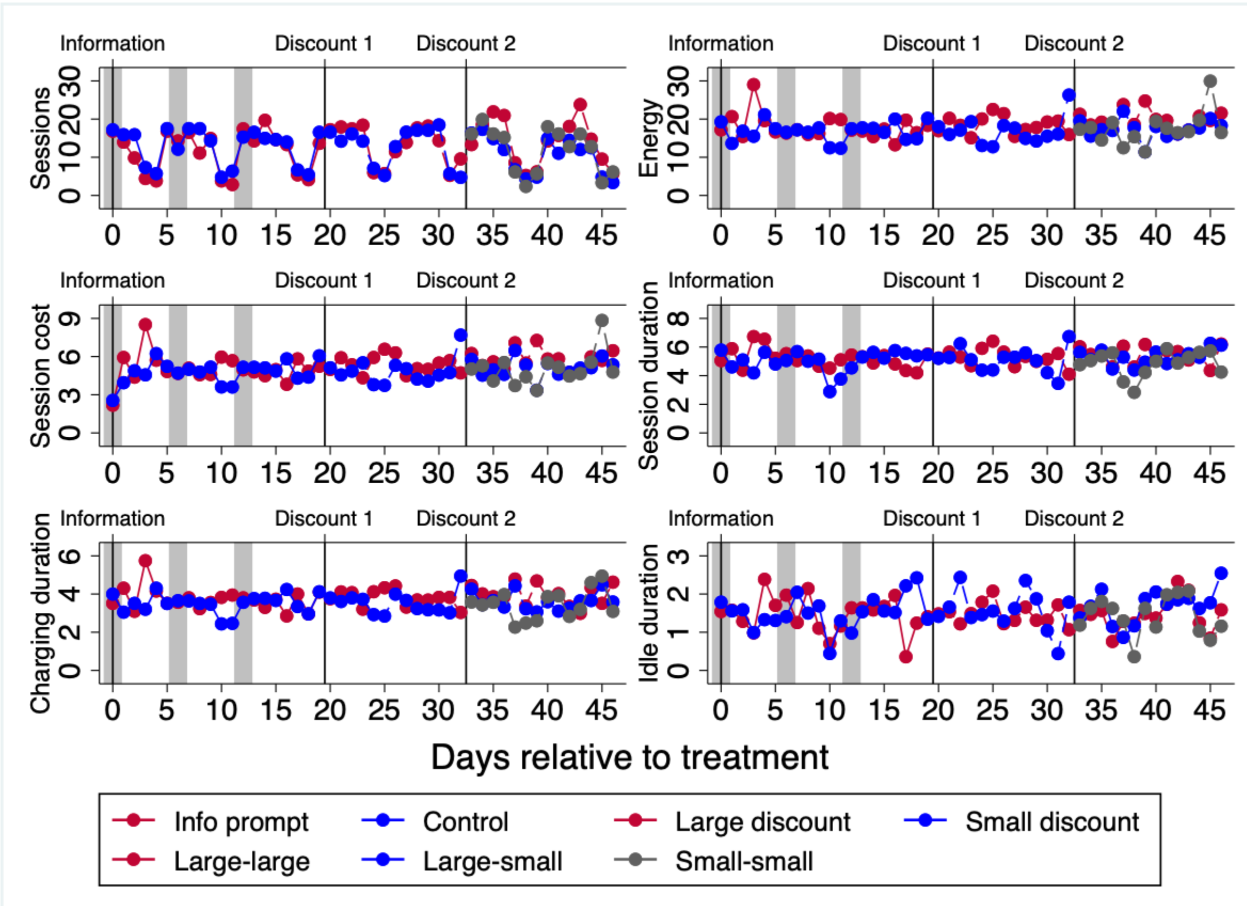


Figure II: Total charging behavior by day

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.

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 E).[15] Second, financial discounts for workplace charging do not change individuals' total charging activity.[16] This is consistent with the lack of a significant increase in charging sessions and energy on the Clean Air Day (Appendix A.7).[17] 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 durations, which suggests that the larger discounts are associated with longer sessions (Table D1).[18] 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.

The absence of significant shifts to campus charging may reflect drivers' perceptions of charger scarcity and unreliability (Appendix C.2; Figure C9).[19] The UCSD charging network typically experiences high weekday utilization of 50—85% by 9 am across all five campus zones (Figure C5).[20] In addition, for both charger vendors, chargers exhibit a 15-20% "glitch" rate (Figure C9) — wherein drivers attempt to initiate a session but ultimately fail, which might stem from errors with the physical charger, in processing payment, or with device or app connectivity.[21]

[15] 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.

[16] 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.

[17] 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.

[18] 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.

[19] In the Triton Chargers enrollment survey, drivers identified difficulties finding an available charger as a primary barrier to charging on campus.

[20] The observed 80% utilization rate assumes 100% charger operability, but chargers experience downtime before repair, which is not captured in our data. 80% is therefore an underestimate of true utilization.

[21] On October 15 and 16, for instance, nearly all PowerFlex sessions involved a glitch.

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	.449	-.046	-3.271	-1.031	-74.408	-42.454	-31.966
	(3.829)	(.271)	(5.426)	(1.503)	(100.903)	(67.588)	(48.551)
Mean Dep. Var.	29.11	2.44	41.96	11.7	756.78	530.94	225.84
B. Financial incentive 1	-3.983	-.006	5.399	1.554	43.169	50.708	-7.536
	(4.487)	(.208)	(4.000)	(1.159)	(68.390)	(49.185)	(29.258)
Mean Dep. Var.	32.88	1.72	30.3	8.76	534.04	380.26	153.78
C. Financial incentive 2	-.687	.434*	7.679	2.271	131.944	94.374	37.605
	(5.406)	(.254)	(5.885)	(1.717)	(94.681)	(69.726)	(39.621)
Mean Dep. Var.	29.2	1.72	31.12	9.04	543.93	380.73	163.2
D. Information x large discount	-3.724	-.021	-1.058	-.366	-107.299	-38.992	-68.325
	(4.066)	(.481)	(9.148)	(2.562)	(170.474)	(116.861)	(81.669)
Observation	313	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.

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).[22] 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 (Panel B) shifts charging to 5–7 am. 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 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.

[22]Analogous results for the other measures of total charging, e.g. cost and duration, are given in Figure C10.

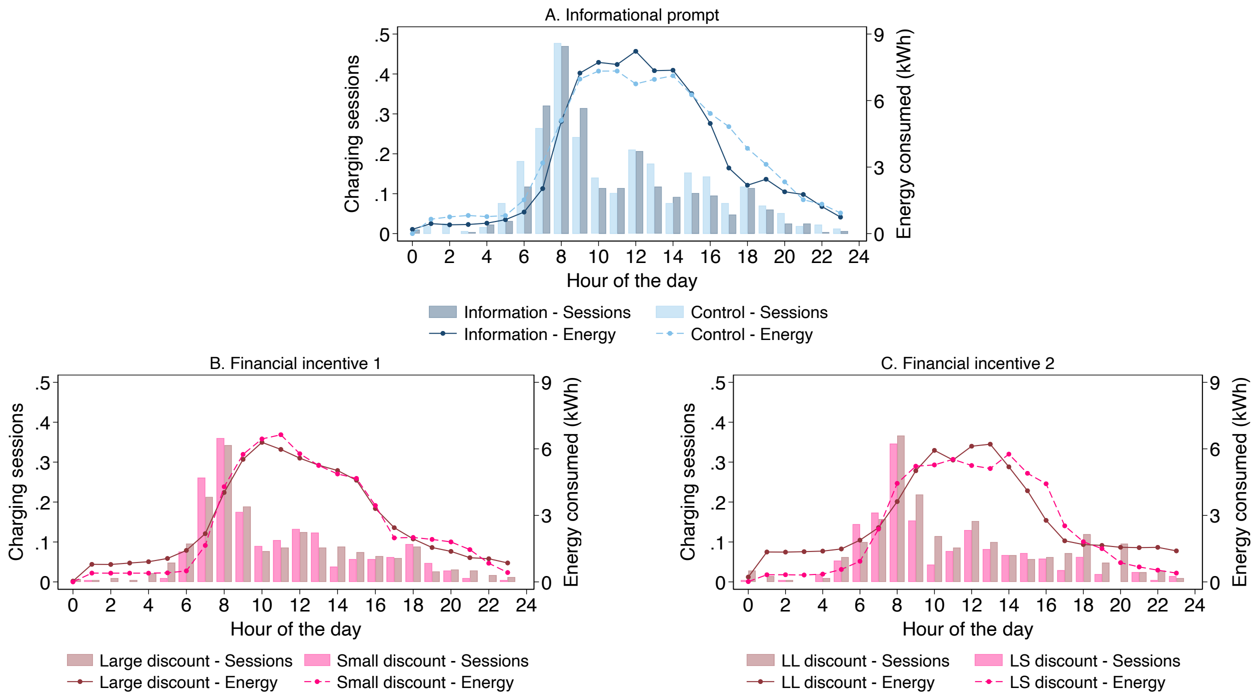


Figure III: Number of charging sessions and energy consumed by hour of the day

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. These substitution patterns hold for both charger vendors (Table D11). This is consistent with charging behavior during the Clean Air Day, which saw drivers initiate earlier charging sessions.[23]

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. The shift to evening sessions also causes longer session and idle duration (Table D1).

Although it is difficult to assess the mechanisms behind our empirical results, concerns about the availability of chargers may partly explain these temporal shifts. First, scarcity concerns are consistent with the shift away from early morning sessions observed during the informational treatment, as these shifts to later morning occurred primarily in campus zones with lower network utilization. Second, the shift toward overnight and early morning charging sessions during the first discount may be because the financial discounts intensify competition for chargers, prompting drivers to arrive earlier to work to increase the likelihood of accessing a charger. Third, as the pool of drivers receiving the large discount was halved in the second financial treatment, the shift to overnight and early morning sessions becomes insignificant, which may be explained by less competition early in the morning, i.e. drivers who learn over time that such early morning arrivals are notnecessary to secure a charger. 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.[24] The shift to evening sessions among the LL group could reflect that could indicate drivers observing high charger availability and adjusting their charging routines to periods with consistently lower network utilization. The shift to midday sessions could reflect that drivers' require time to internalize the discounts before adjusting their charging behavior.

III.C Heterogeneous response to interventions

We observe substantial heterogeneity in the timing of charging among experimental subgroups. Understanding differing responses among different groups is important because policymakers can target interventions toward the most receptive individuals. We find that commuting distance, university affiliation, home charger access, modal price paid for charg-

[23]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.

[24]As our study occurred over a relatively short timeframe and given that drivers charge, on average, roughly oncer per week, our estimated treatment effects should be interpreted as short-term effects, which require a longer horizon to form charging habits.

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	-.133*	.158	-.034	.011
	(.046)	(.080)	(.174)	(.142)	(.082)
Mean Dep. Var.	.09	.2	1.02	.76	.37
B. Financial incentive 1	.072**	.073*	-.069	-.045	-.037
	(.034)	(.042)	(.126)	(.106)	(.063)
Mean Dep. Var.	.07	.12	.74	.51	.26
C. Financial incentive 2	.051	-.061	.050	.226*	.229**
	(.068)	(.081)	(.134)	(.135)	(.095)
Mean Dep. Var.	.07	.18	.68	.64	.26
D. Information x large discount	-.070	-.148	.136	.057	.005
	(.079)	(.110)	(.319)	(.230)	(.142)
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.

ing, environmental attitudes, and vehicle type impact the responses to our interventions (Appendix D.3). The informational treatment leads to a shift to early morning charging sessions among short commuters, students, and individuals who report paying high prices for charging. Conversely, financial discounts lead to shifts toward early morning and overnight charging sessions among distant commuters, staff, individuals without home chargers, and those with lower environmental motivations.

Short commuters (those with one-way commutes of < 7.5 miles) switch most frequently to early morning (5–7) charging as a response to the informational prompts, whereas distant commuters (one-way commutes of > 25 miles) arrive earlier to campus and charge overnight (21–5) as a response to the financial discounts (Table D12). Frequent commuters (those who commute ≥ 3 times per week) are largely responsible for the shift to early morning and overnight sessions as a response to the first discount and to evening (16–21) sessions as a response to the second discount (Table D13). In addition, the information and financial treatment induce mainly students to reduce early morning and increase evening charging sessions (Table D14). Short-commuters, frequent commuters, and students have potentially greater flexibility in their daily schedules, and therefore may be more able or inclined to adapt their commuting times.[25] In contrast, distant commuters, who comprise a larger share of staff and faculty, who work more regular hours (9 am to 5 pm), may have less flexible schedules. Moreover, we observe that low-income individuals (i.e., students) shift to overnight sessions, which is consistent with the temporal shifts among students (Table D15).[26] Providing financial discounts to individuals without a home charger or those who report paying high modal prices for charging induces large shifts to evening and overnight charging sessions (Table D16 and D17). Individuals who report high environmental motivations for charging do not significantly shift to midday sessions during the informational treatment, while individuals who report low environmental motivations increase their overnight, early morning, and midday charging as a response to financial discounts (Table D18). One possible explanation is that the information causes a larger shift among individuals who are ignorant about the climate benefits but that these individuals also have a higher price elasticity of EV charging. Finally, these interventions mainly shift the timing of charging among individuals who drive battery EVs (Table D19), which have larger batteries and require longer charging duration.

[25] The inflexibility of long-distance commuters is supported by Langbroek et al. (2017) showing that those who plan their trips well in advance are less likely to adjust their charging time.

[26] Some students in our sample report a high income, perhaps reflecting parent's income and that they are tax dependents. For instance, 20% of undergrads assert \$150k+ in household income.

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.[27] 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.[28] 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 intemporal shifts in charging and the social cost of carbon (equation 3). Second are revenues earned through the Low Carbon Fuel Standard (LCFS) 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

[27] 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.

[28] Future work can expand on this approach by integrating the shift to campus in addition to the intertemporal shift.

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 $-\$368.66$. We provide further details on welfare calculations in Appendix F.

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**

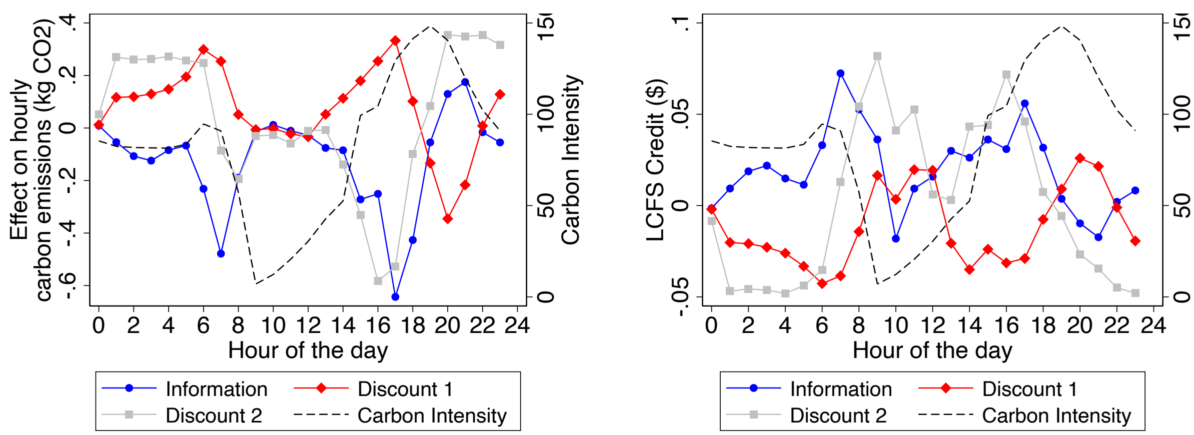
Notes: This table reports the annual welfare effects per driver, from the perspective of the institution, from changes in the timing of charging sessions, per equation (2). Welfare effects are reported for the informational (column 1), first financial (column 2), and second financial treatment (column 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 IVa). 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).[29] 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.

Figure IVa 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 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.[30]



(a) Effect on hourly CO_2 emissions

(b) Effect on hourly LCFS revenues

Figure IV: 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 alter-

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

[30]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.

natives, which reduce petroleum dependency and achieve air quality benefits.[31] 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.

Figure IVb illustrates the effect of each treatment on LCFS revenues. 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 V presents the distributional profile of the financial discounts across six income brackets in our study population. Normalized

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

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.

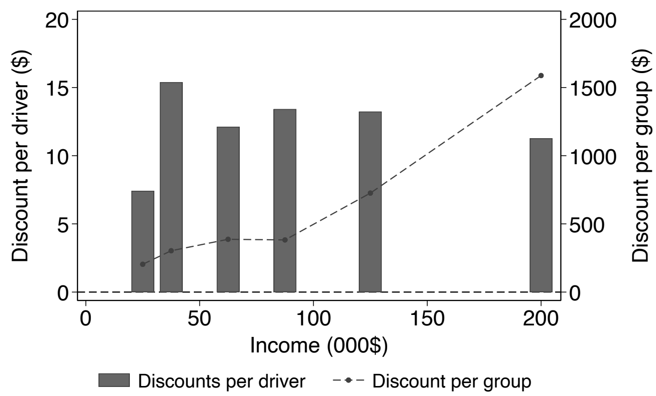


Figure V: Discounts by income

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.[32] 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 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.[33]

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

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

[33] 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.

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, 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.

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Appendix

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

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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), and Clean Air Day (Section A.7).

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

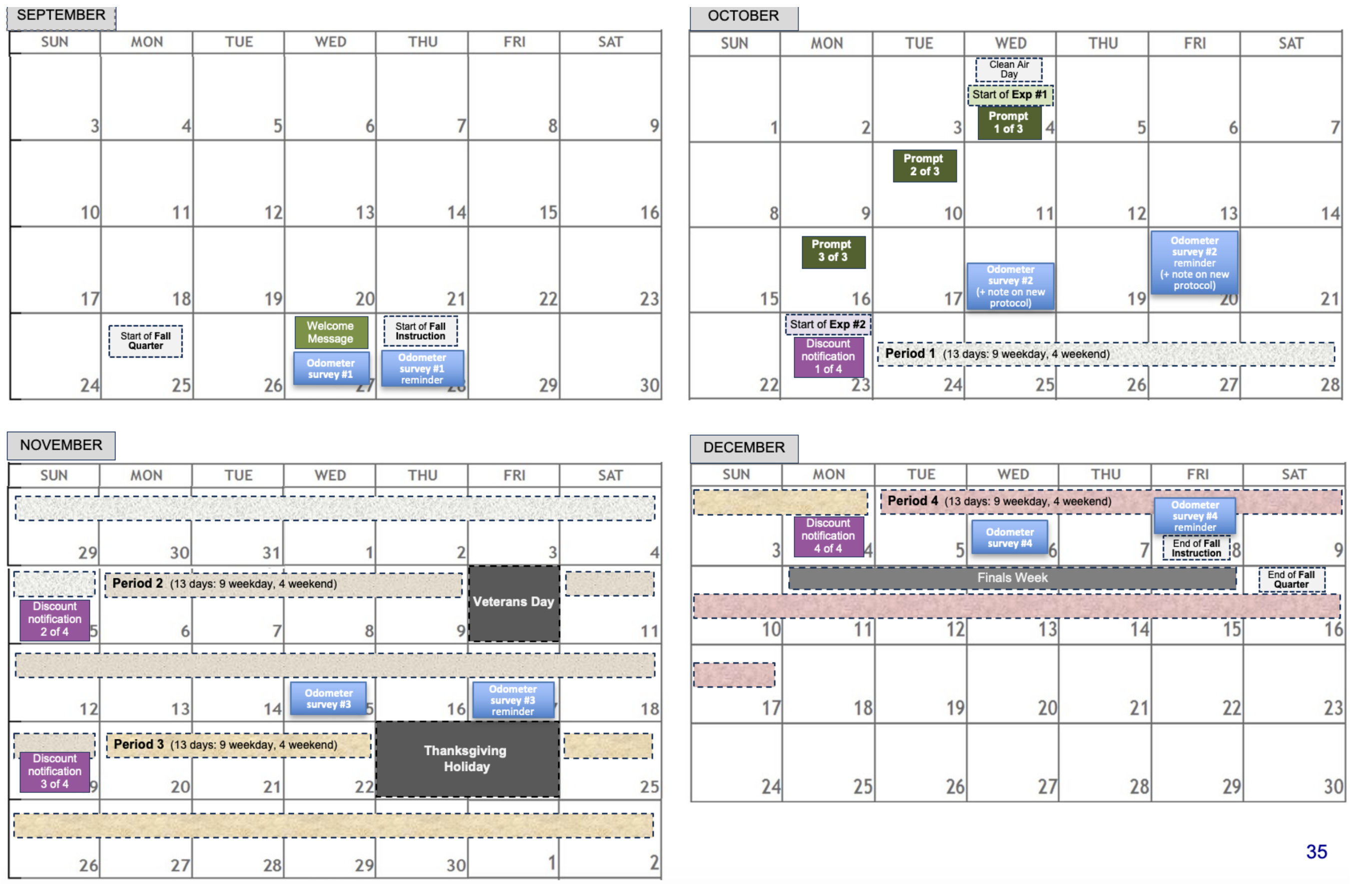


Figure A1: Experimental schedule for the three interventions

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.

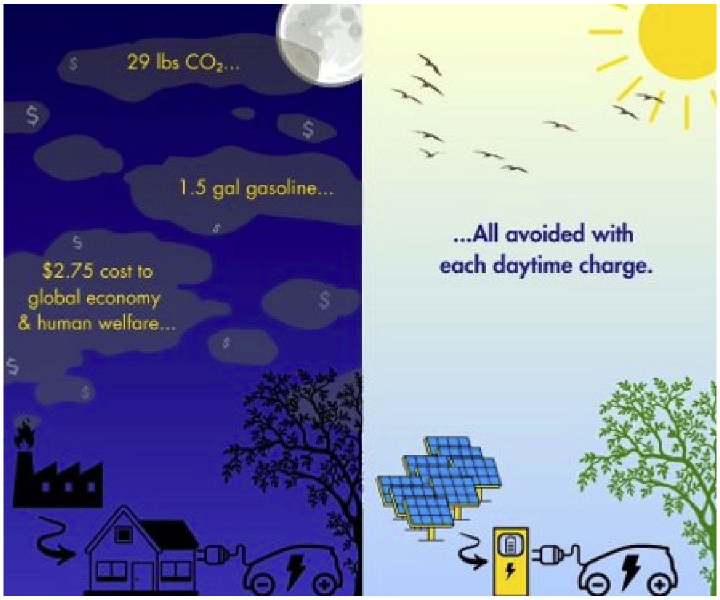


Figure A2: Infographic included with the informational prompt

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 Southern 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 dropdowns.)

- 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]

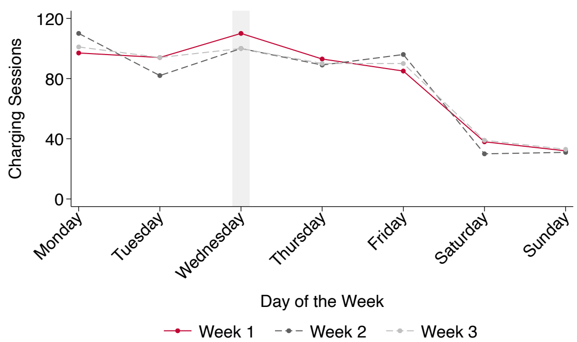
Charging Accounts
23. Click here to set up your ChargePoint account if you don't yet have one or to log in if you do. Enter your ChargePoint ID below.

- a. [Open response]

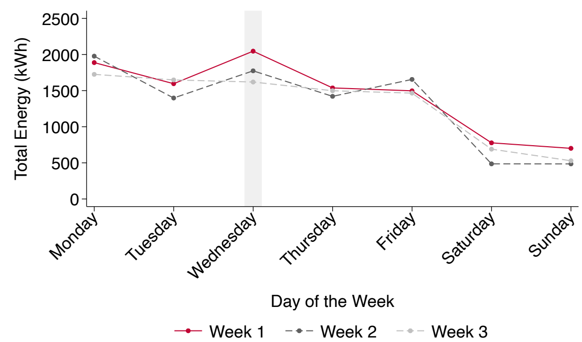
24. Click here to set up your PowerFlex account and download the Smartphone app if you haven't yet. Enter the email address associated with your PowerFlex account below.

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

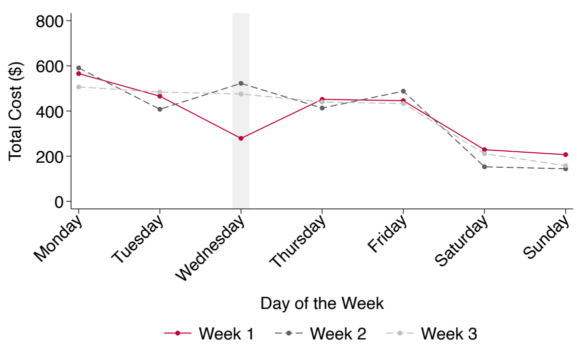
A.7 Clean Air Day



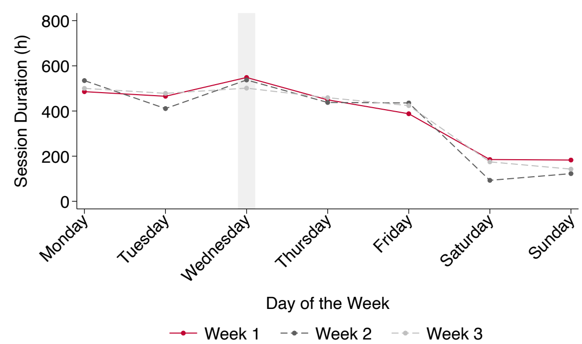
(a) Number of charging sessions



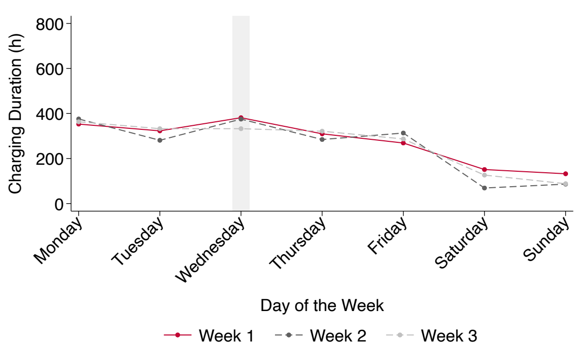
(b) Total energy



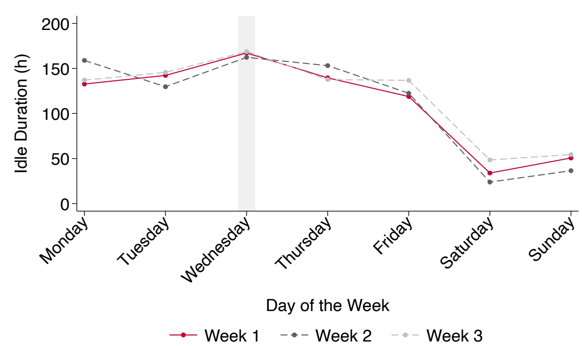
(c) Total costs



(d) Charging duration



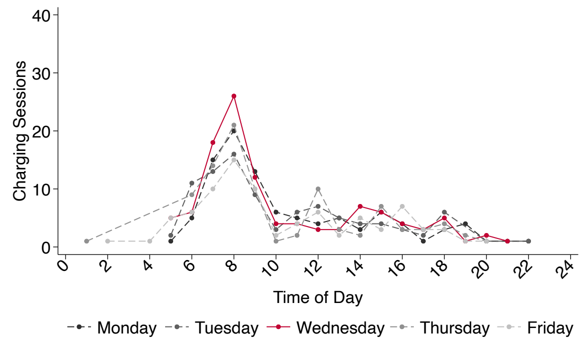
(e) Charging duration



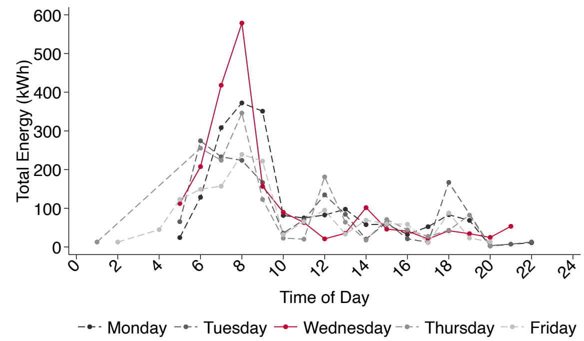
(f) Idle duration

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

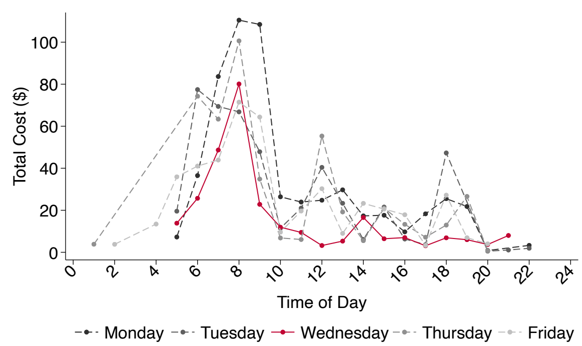
Notes: This figure shows the charging activity of the Triton Chargers EV club during the first three weeks of October by day of the week. Shown are the number of charging sessions (Panel A), energy consumed (Panel B), session cost (Panel C), session duration (Panel D), charging duration (Panel E), and 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.



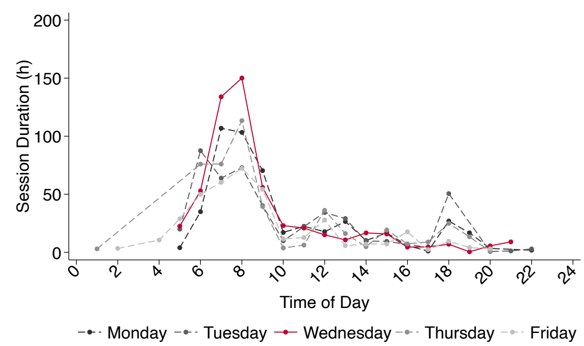
(a) Number of charging sessions



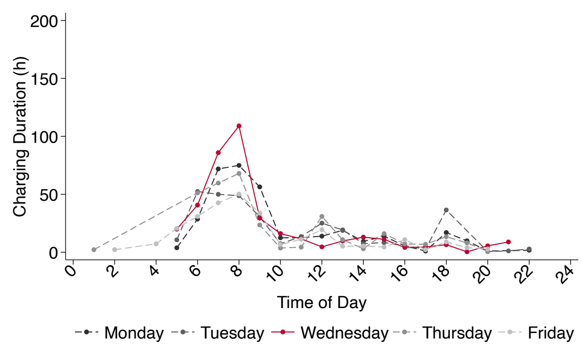
(b) Total energy



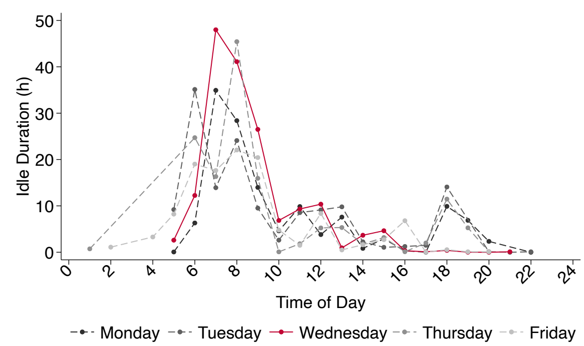
(c) Total costs



(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..

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).[34]

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.

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

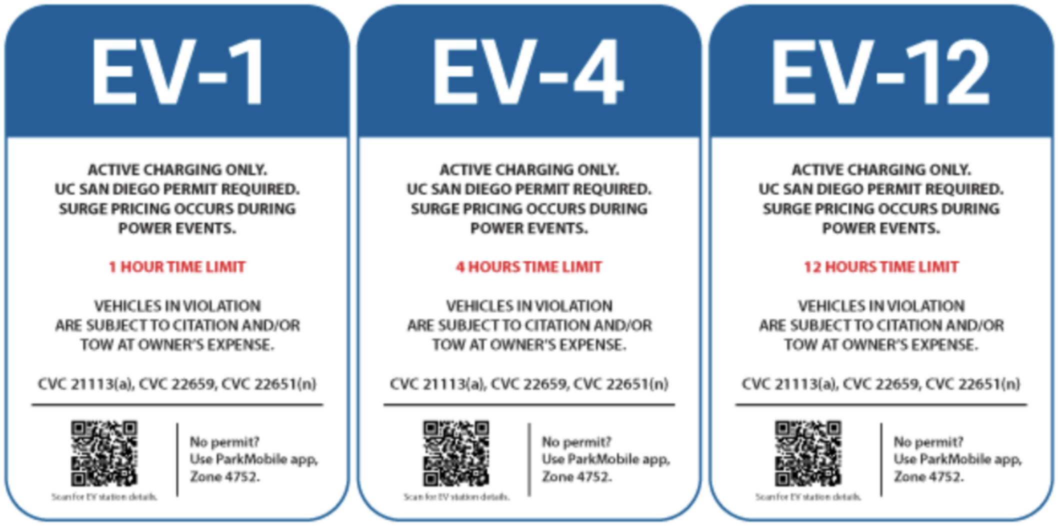


Figure B1: Type of parking stalls at UCSD

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.

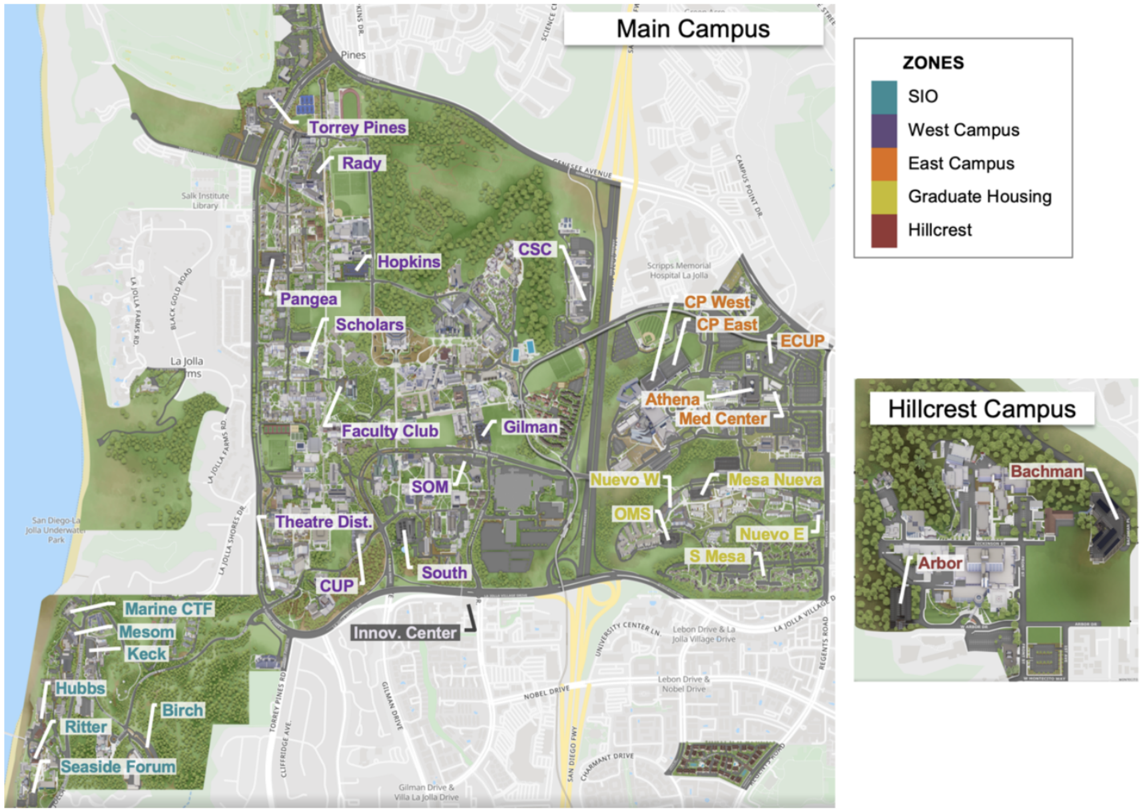


Figure B2: Parking zones and plazas at UCSD

Notes: This figure shows the five distinct parking zones and individual plazas / 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

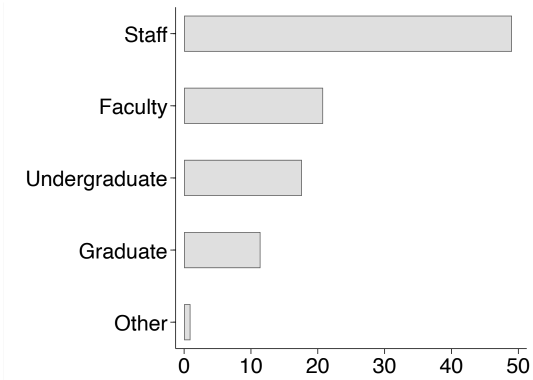
Table B4: Average carbon intensity (gCO2/MJ) of the California power grid

	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

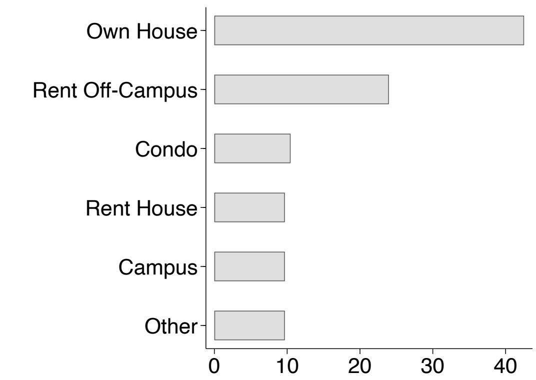
Notes: The table presents the California Air Resources Board (CARB) Low Carbon Fuel Standard (LCFS) quarterly carbon intensity values, in gCO2/MJ, for smart charging and electrolysis in 2022.

C Supplementary descriptive statistics

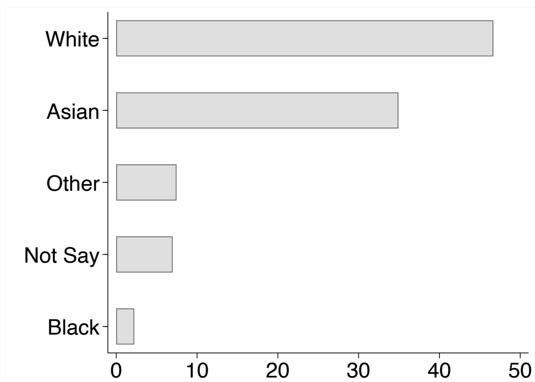
C.1 Triton Charger EV club enrollment survey results



(a) University affiliation



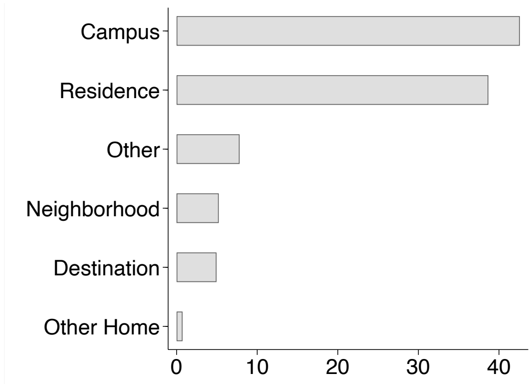
(b) Living Arrangement



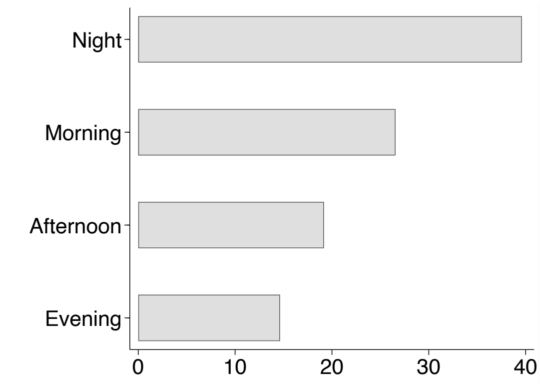
(c) Race

Figure C1: Demographics

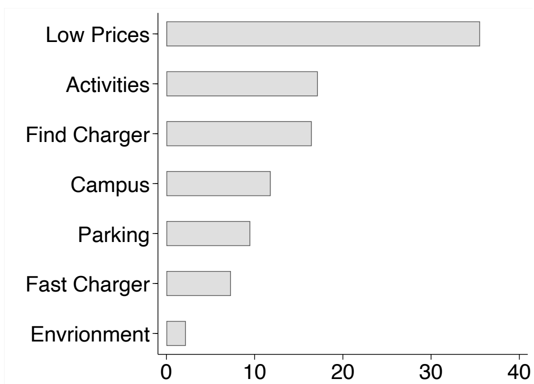
Notes: The figure presents summary statistics for demographic variables of the Triton Charger Club.



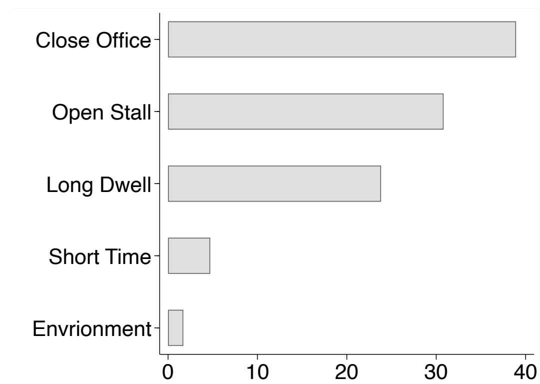
(a) Charging Location



(b) Charging Time



(c) Charging Motivation



(d) Motivation Campus Charging

Figure C2: Charging Motivation

Notes: The figure present the the motivation for charging.

C.2 UCSD EV network utilization

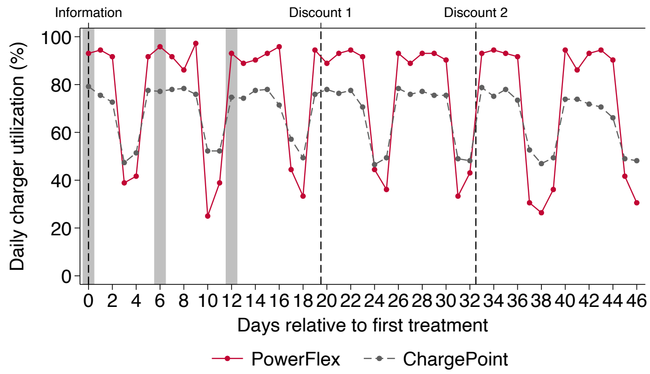
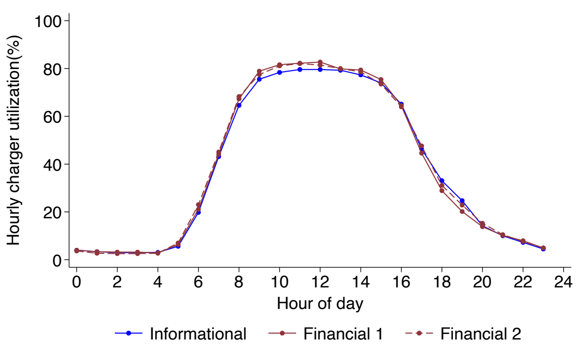
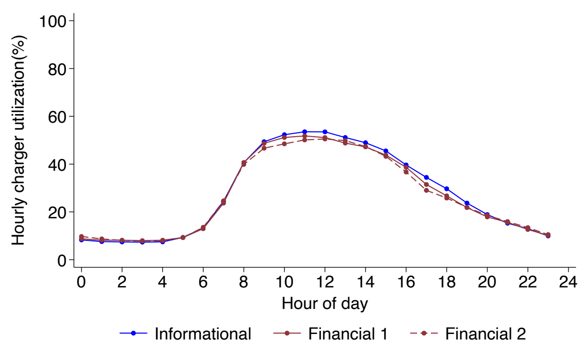


Figure C3: Network utilization by day

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. Utilization, as presented here, does not consider inoperable (broken) chargers; including those would decrease the effective number of chargers and increase utilization.



(a) PowerFlex



(b) ChargePoint

Figure C4: Network utilization by time of day and vendor

Notes: This figure shows hourly utilization of PowerFlex (Panel A) and ChargePoint (Panel B) charger during the informational, first financial and second financial treatment. We define hourly charger utilization as the percentage of chargers used in a given hour relative to all chargers used during the experiment period (October 4 - November 19).

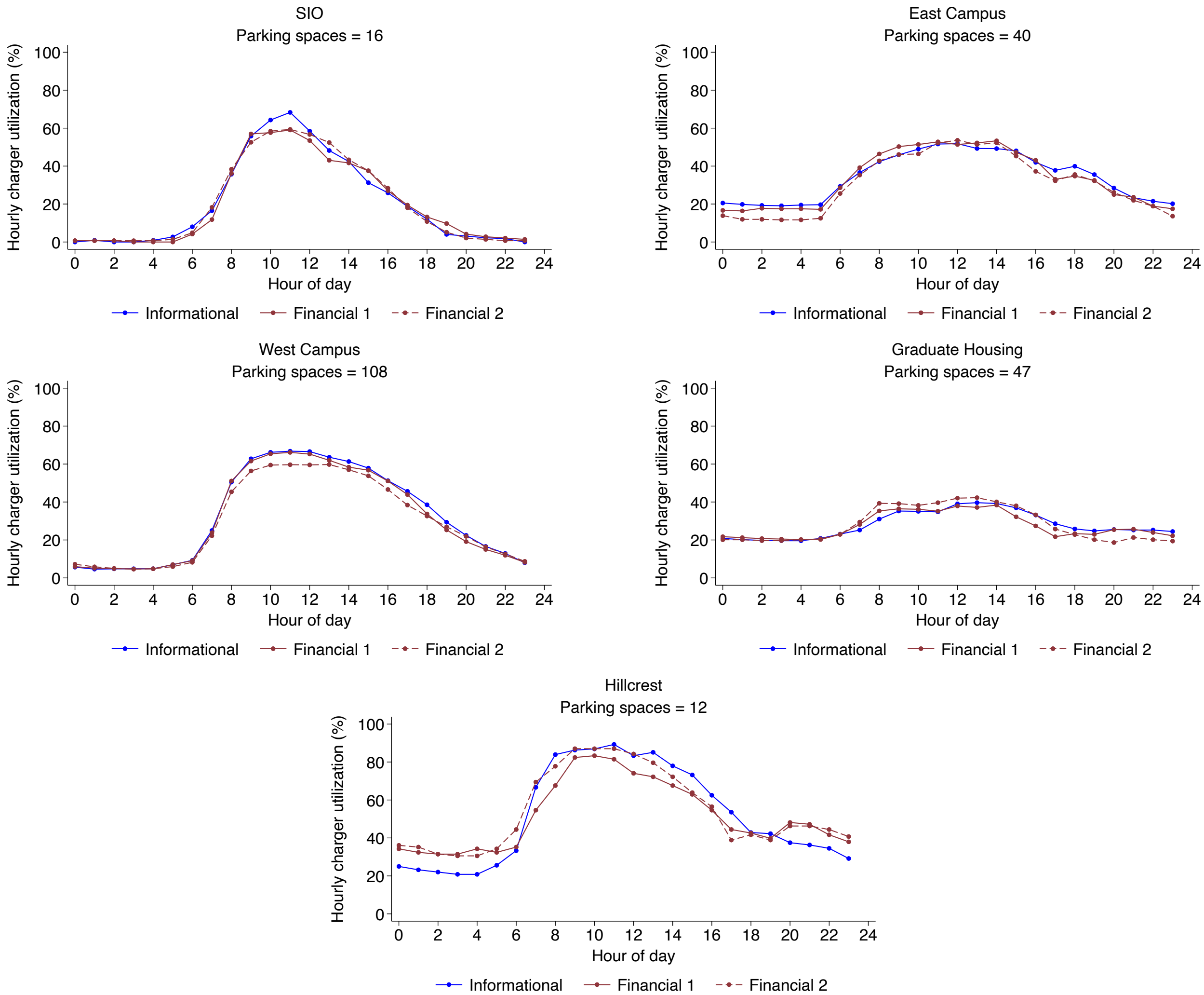


Figure C5: Network utilization by time of day and campus zone

Notes: This figure shows hourly utilization of ChargePoint chargers for the five campus zones over the experiment period (October 4 - November 19). We define hourly charger utilization as the percentage of chargers used in a given hour relative to all chargers used during the experiment period.

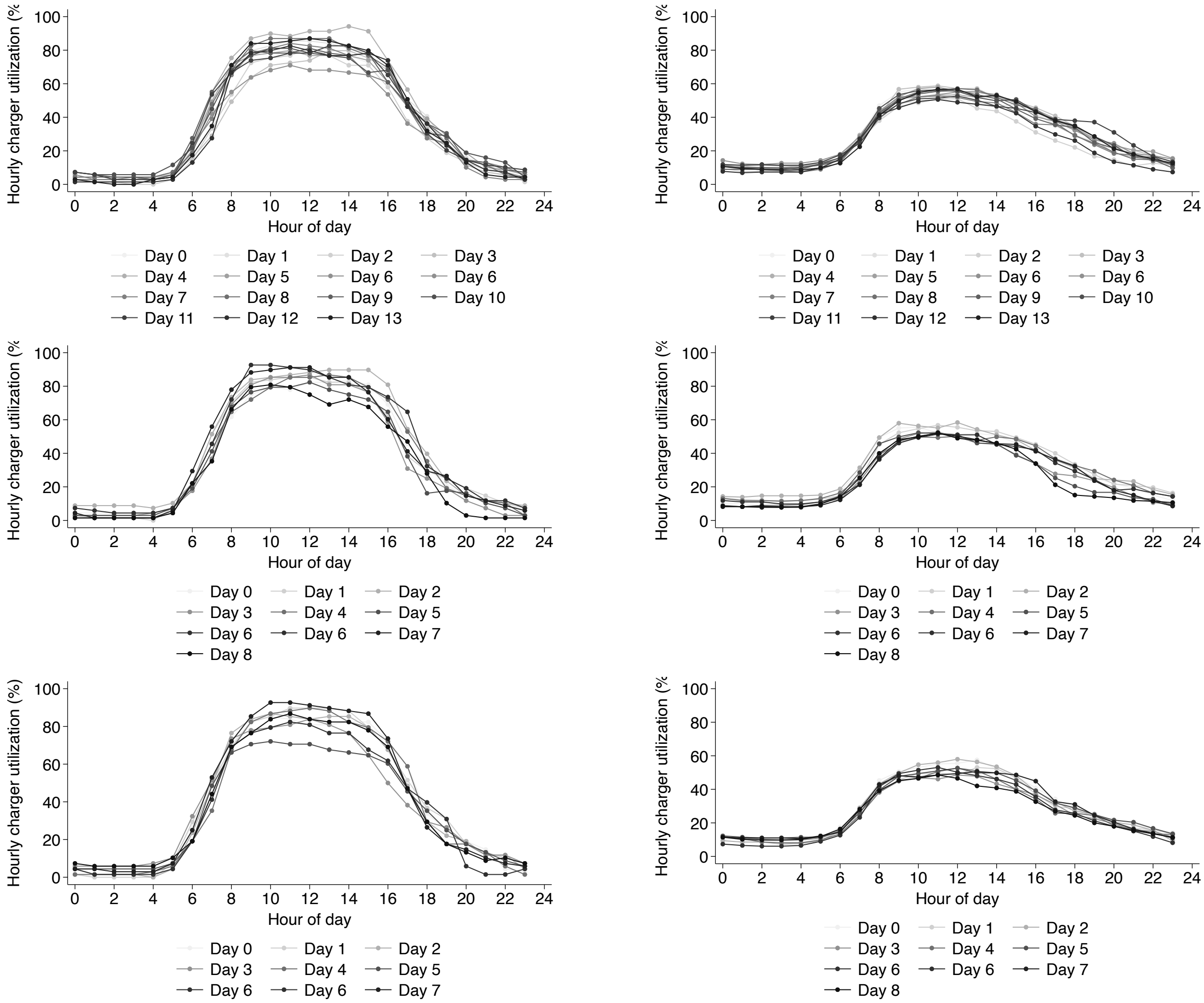


Figure C6: Network utilization by time of day and day

Notes: This figure shows hourly utilization of PowerFlex and ChargePoint chargers by day over the experiment period (October 4 - November 19). We define hourly charger utilization as the percentage of chargers used in a given hour relative to all chargers used during the experiment period.

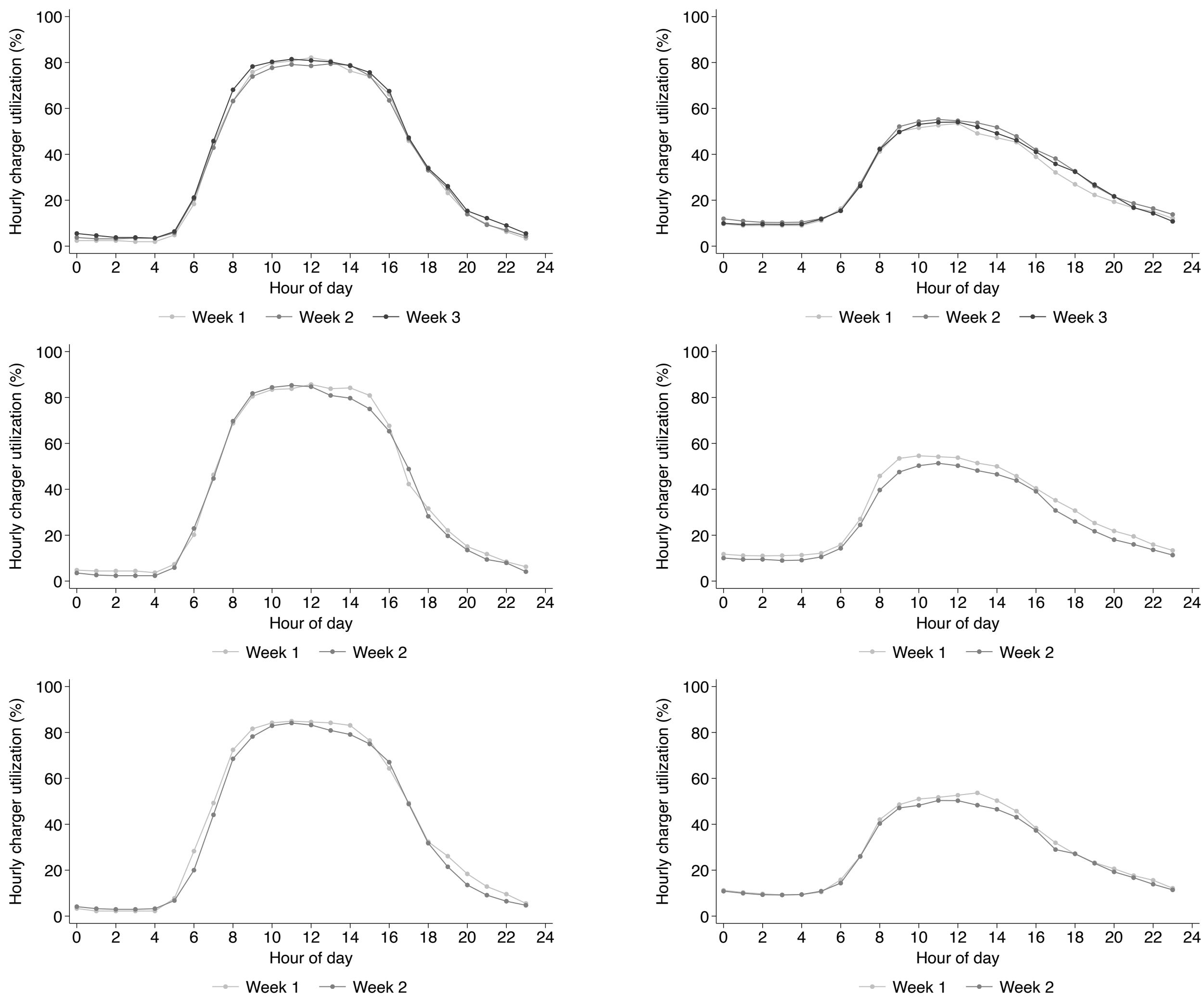


Figure C7: Network utilization by time of day and week

Notes: This figure shows hourly utilization of PowerFlex and ChargePoint chargers for different weeks 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.

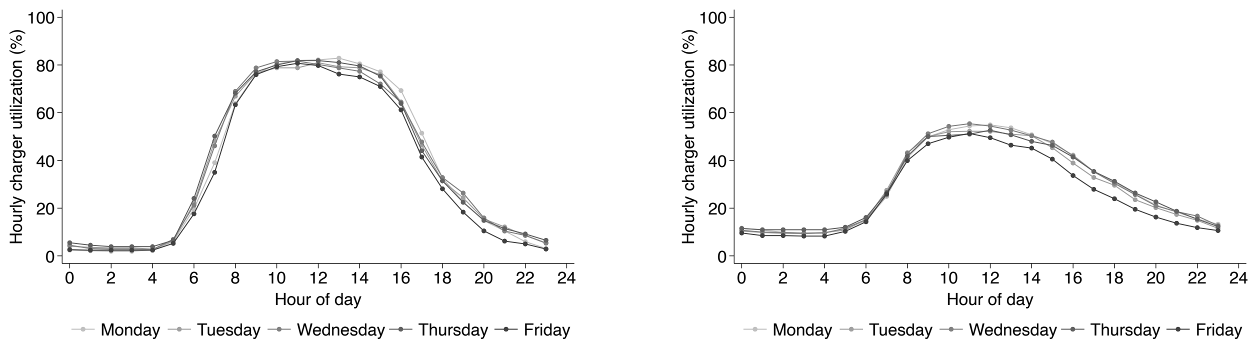


Figure C8: Network utilization by day of the week

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.3 Charger glitches

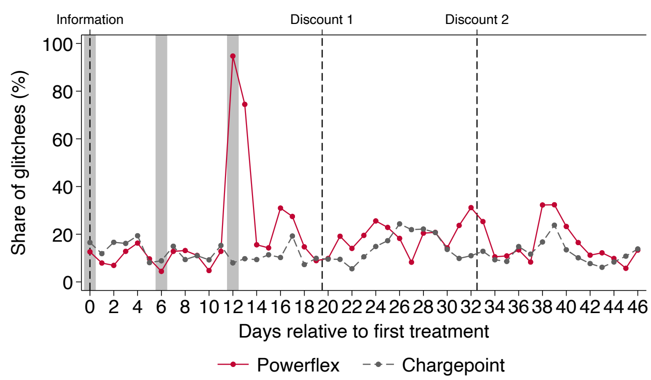


Figure C9: Charger glitching

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 10 minutes or consumes less than 1 kWh. Vertical dashed lines denote the start of each intervention; thick gray lines denote days on which the informational prompt was sent.

C.4 Timing of charging activities

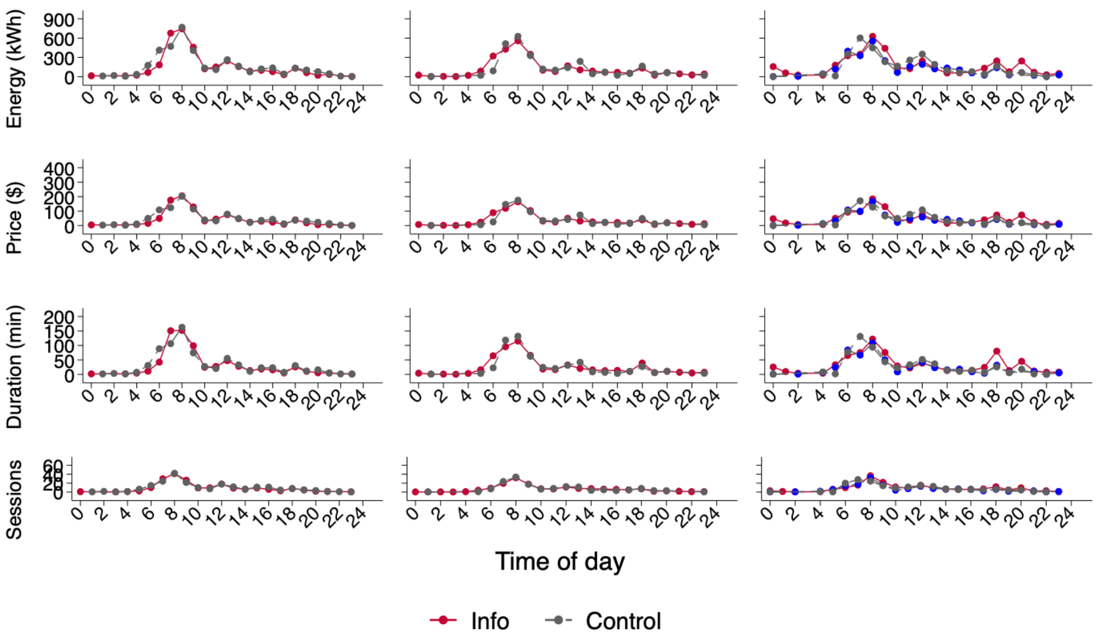


Figure C10: Total charging behavior by hour of the day

Notes: This figure shows the study participant charging activity 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).

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	-.687	-.197	-9.685	-4.608	-5.076
	(1.083)	(.301)	(17.275)	(13.003)	(7.715)
Mean Dep. Var.	9.96	2.77	170.04	123.59	46.44
B. Financial incentive 1	1.707	.493	17.257	15.325	1.930
	(1.123)	(.325)	(17.504)	(13.330)	(6.947)
Mean Dep. Var.	9.68	2.8	157.79	117.99	39.8
C. Financial incentive 2	1.596	.432	37.861*	17.951	19.927*
	(1.408)	(.413)	(21.995)	(16.178)	(10.713)
Mean Dep. Var.	10.03	2.91	166.62	118.21	48.4
D. Information x large discount	-1.213	-.316	-24.614	-17.554	-7.057
	(1.083)	(.308)	(17.690)	(13.093)	(8.095)
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	3.316	.113	1.115	.307	-2.801	15.085	-17.897
	(2.852)	(.157)	(4.160)	(1.057)	(81.936)	(53.344)	(38.745)
ChargePoint	-2.269	-.159	-4.385	-1.338	-71.607	-57.539	-14.069
	(3.645)	(.244)	(4.321)	(1.273)	(73.624)	(51.372)	(32.189)
B.Financial incentive 1							
PowerFlex	.918	.027	2.682	.736	7.595	14.233	-6.635
	(3.053)	(.104)	(2.533)	(.675)	(49.167)	(35.354)	(18.554)
ChargePoint	-4.898	-.033	2.717	.818	35.574	36.475	-.901
	(4.444)	(.193)	(3.455)	(1.037)	(53.436)	(38.956)	(23.055)
C.Financial incentive 2							
PowerFlex	-2.229	.124	1.470	.400	38.246	15.896	22.385
	(3.242)	(.130)	(3.201)	(.843)	(59.260)	(36.155)	(29.064)
ChargePoint	.901	.310	6.209	1.871	93.698	78.478	15.220
	(5.148)	(.232)	(5.315)	(1.598)	(80.860)	(63.312)	(29.347)
D.Interaction							
PowerFlex	.076	.075	1.475	.428	-12.660	8.055	-20.732
	(3.029)	(.276)	(6.869)	(1.784)	(138.608)	(91.225)	(66.096)
ChargePoint	-4.556	-.095	-2.533	-.794	-94.639	-47.047	-47.592
	(3.619)	(.430)	(7.459)	(2.197)	(123.680)	(89.287)	(52.385)

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 commute distance

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Short Commute	5.586	-.420	-15.888**	-4.297**	-275.542**	-198.065**	-77.478
	(6.855)	(.373)	(6.363)	(1.797)	(117.205)	(77.876)	(53.918)
Medium Commute	3.530	-.064	.033	-.227	-35.779	-37.469	1.693
	(5.726)	(.342)	(6.985)	(1.926)	(132.614)	(83.977)	(70.880)
Long Commute	-6.179	.314	4.620	1.067	66.589	93.608	-27.055
	(5.210)	(.447)	(8.773)	(2.437)	(159.649)	(112.692)	(71.716)
B.Financial incentive 1							
Short Commute	-7.956	-.156	.314	.266	-27.716	-25.773	-1.941
	(7.584)	(.263)	(5.237)	(1.535)	(84.010)	(61.164)	(35.712)
Medium Commute	-.992	.048	5.915	1.776	58.382	54.338	4.073
	(5.529)	(.263)	(5.110)	(1.480)	(92.720)	(67.041)	(40.641)
Long Commute	-4.791	.092	9.993*	2.628	99.417	123.837*	-24.441
	(5.582)	(.286)	(5.864)	(1.681)	(103.629)	(73.839)	(45.952)
C.Financial incentive 2							
Short Commute	-5.560	.626*	9.506	3.008	177.658	105.776	71.919
	(8.348)	(.353)	(11.377)	(3.392)	(144.200)	(118.615)	(50.705)
Medium Commute	8.287	.594*	8.386	2.277	158.159	113.256	44.952
	(7.105)	(.347)	(7.492)	(2.178)	(131.477)	(99.839)	(54.088)
Long Commute	-7.139	.096	5.283	1.590	63.349	64.719	-1.350
	(6.656)	(.417)	(7.812)	(2.269)	(136.156)	(95.981)	(58.239)

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. A short commute is <7.5 miles, one-way; medium commute, <7.5 and >15 miles; and long commute, >15 miles. 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 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	-3.278	.095	-5.463	-1.528	-160.094	-67.700	-92.393*
	(5.993)	(.353)	(6.645)	(1.849)	(115.050)	(79.554)	(50.959)
Frequent Commute	2.314	-.113	-2.229	-.795	-33.677	-30.453	-3.242
	(4.718)	(.342)	(6.701)	(1.855)	(124.590)	(83.127)	(60.087)
B.Financial incentive 1							
Infrequent Commute	-5.682	-.192	-2.577	-.829	-102.131	-58.949	-43.168
	(6.296)	(.254)	(5.240)	(1.515)	(86.006)	(63.511)	(34.416)
Frequent Commute	-2.967	.090	9.515*	2.784*	118.162	107.305	10.855
	(5.678)	(.261)	(5.230)	(1.531)	(89.882)	(66.648)	(37.123)
C.Financial incentive 2							
Infrequent Commute	-16.566**	.078	-5.510	-1.630	-6.492	-52.105	45.621
	(6.674)	(.322)	(5.893)	(1.749)	(98.678)	(70.668)	(44.432)
Frequent Commute	7.319	.608*	14.100*	4.171*	199.344	165.689*	33.703
	(6.330)	(.316)	(8.366)	(2.456)	(130.134)	(97.004)	(53.080)

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 D5: Effect on total charging behavior by affiliation

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Student	6.707	.265	-10.028	-2.715	-206.808	-130.123	-76.709
	(8.019)	(.512)	(7.472)	(2.162)	(128.525)	(90.973)	(55.258)
Faculty	-12.329**	-1.126***	-20.245***	-5.455***	-377.006***	-279.756***	-97.241
	(5.869)	(.351)	(7.181)	(2.019)	(129.773)	(89.116)	(64.304)
Staff	1.612	.149	4.586	.994	93.167	68.888	24.292
	(4.688)	(.335)	(7.495)	(2.069)	(139.416)	(92.720)	(66.861)
B.Financial incentive 1							
Student	-10.674	.094	-.239	-.013	-67.633	-46.719	-20.907
	(7.941)	(.327)	(6.097)	(1.797)	(97.828)	(70.863)	(41.924)
Faculty	-10.212	-.741***	-13.938***	-3.836**	-197.878**	-187.419***	-10.466
	(7.484)	(.283)	(5.278)	(1.520)	(100.184)	(64.766)	(50.819)
Staff	-.201	.117	11.976**	3.431**	144.850*	149.004**	-4.142
	(4.838)	(.235)	(4.906)	(1.411)	(87.702)	(64.556)	(36.516)
C.Financial incentive 2							
Student	-4.119	.750	8.684	2.537	102.914	66.613	36.325
	(9.465)	(.536)	(12.490)	(3.721)	(162.076)	(134.831)	(55.404)
Faculty	-8.458	.363	-3.687	-.629	-6.268	-51.043	44.857
	(7.668)	(.403)	(7.153)	(2.214)	(132.621)	(88.289)	(68.733)
Staff	4.008	.303	11.363	3.204	211.725	168.794*	42.963
	(6.306)	(.267)	(7.402)	(2.135)	(128.672)	(93.783)	(51.828)

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 affiliation. 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 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 income

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Low Income	7.457	-.725	-10.911	-3.442	-284.260*	-158.710	-125.545**
	(8.072)	(.529)	(9.249)	(2.642)	(154.067)	(113.573)	(59.173)
Medium Income	3.533	.362	-1.697	-.580	17.413	13.748	3.658
	(6.101)	(.442)	(7.834)	(2.173)	(143.800)	(100.916)	(62.767)
High Income	-5.245	.170	1.124	.385	14.715	3.452	11.237
	(5.097)	(.378)	(7.608)	(2.069)	(148.072)	(92.920)	(80.032)
B.Financial incentive 1							
Low Income	-12.679	.308	10.893	3.076	161.739	120.745	40.958
	(8.185)	(.339)	(7.193)	(2.096)	(112.395)	(85.783)	(43.131)
Medium Income	-3.525	-.089	3.882	1.197	81.852	89.093	-7.225
	(7.089)	(.273)	(5.698)	(1.663)	(104.032)	(81.993)	(36.750)
High Income	1.296	-.203	1.988	.566	-79.010	-32.028	-46.957
	(6.304)	(.309)	(5.732)	(1.648)	(100.347)	(67.566)	(47.703)
C.Financial incentive 2							
Low Income	-2.249	.829*	17.081	5.056	275.074*	213.444	61.618
	(8.950)	(.494)	(12.840)	(3.811)	(162.623)	(137.555)	(48.814)
Medium Income	-8.519	.285	1.129	.379	140.795	74.431	66.427
	(8.400)	(.346)	(7.295)	(2.146)	(151.874)	(115.090)	(64.549)
High Income	4.480	.226	4.652	1.345	16.623	15.855	.823
	(6.815)	(.314)	(7.299)	(2.130)	(124.269)	(81.943)	(57.878)

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 income. Low income refers to less than $100k, medium income $100-$200k, and high income above $200k. 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 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 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	2.590	-.172	-7.532	-2.390	-104.780	-52.416	-52.370
	(4.494)	(.345)	(6.719)	(1.854)	(133.509)	(82.747)	(69.520)
No Home Charger	-3.663	.143	3.139	1.013	-28.724	-27.471	-1.275
	(7.492)	(.466)	(8.921)	(2.493)	(151.974)	(115.703)	(57.111)
B.Financial incentive 1							
Home Charger	-1.745	.100	7.825	2.210	36.470	68.902	-32.430
	(5.298)	(.244)	(4.791)	(1.389)	(88.385)	(58.559)	(42.783)
No Home Charger	-7.835	-.154	2.015	.638	52.511	25.331	27.183
	(7.682)	(.378)	(6.809)	(1.982)	(112.928)	(87.191)	(42.007)
C.Financial incentive 2							
Home Charger	-.454	.276	7.118	2.228	98.247	81.333	16.936
	(6.113)	(.277)	(7.630)	(2.235)	(114.580)	(83.552)	(48.092)
No Home Charger	-1.111	.666	8.502	2.335	181.378	113.505	67.929
	(8.606)	(.426)	(8.570)	(2.519)	(145.327)	(110.423)	(59.712)

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 D8: 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	2.141	-.371	-.243	-.425	-23.175	-21.902	-1.294
	(6.217)	(.341)	(8.244)	(2.380)	(137.340)	(94.060)	(64.446)
Medium Charge Rate	-1.521	-.016	-4.530	-1.141	-97.404	-57.029	-40.379
	(4.420)	(.322)	(6.157)	(1.719)	(112.675)	(76.678)	(55.101)
High Charge Rate	4.871	.185	-2.703	-1.312	-60.139	-21.890	-38.274
	(8.290)	(.531)	(10.339)	(2.791)	(185.994)	(127.399)	(80.528)
B.Financial incentive 1							
Low Charge Rate	-2.213	-.589**	-5.315	-1.734	-97.415	-69.827	-27.600
	(6.779)	(.287)	(5.271)	(1.521)	(99.498)	(64.537)	(51.235)
Medium Charge Rate	-3.540	.106	6.208	1.843	77.091	68.617	8.473
	(5.175)	(.237)	(4.543)	(1.320)	(80.205)	(58.168)	(34.551)
High Charge Rate	-7.924	.288	14.839*	4.317*	91.453	128.350	-36.864
	(9.128)	(.385)	(8.465)	(2.447)	(144.005)	(101.837)	(53.903)
C.Financial incentive 2							
Low Charge Rate	-11.211*	.009	-3.059	-1.102	15.009	-33.924	48.947
	(6.189)	(.275)	(5.553)	(1.562)	(105.750)	(67.284)	(53.571)
Medium Charge Rate	-3.117	.496	6.725	2.062	111.961	93.280	18.711
	(5.189)	(.337)	(7.494)	(2.220)	(114.255)	(90.144)	(45.696)
High Charge Rate	.206	.750	23.730	7.028	337.316	253.390	84.003
	(9.544)	(.489)	(15.024)	(4.397)	(249.091)	(169.157)	(95.248)

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 D9: Effect on total charging behavior by environmental motivation

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
High Environmental Motivation	11.962	.075	9.646	1.867	21.546	78.133	-56.614
	(9.635)	(.550)	(11.269)	(3.110)	(200.491)	(131.143)	(110.502)
Low Environmental Motivation	-.999	-.060	-4.785	-1.371	-85.653	-56.585	-29.078
	(3.991)	(.282)	(5.686)	(1.575)	(104.150)	(70.633)	(48.795)
B.Financial incentive 1							
High Environmental Motivation	8.723	.449	21.386**	5.898**	257.640	212.477*	45.150
	(9.718)	(.463)	(10.400)	(2.880)	(160.319)	(119.528)	(62.384)
Low Environmental Motivation	-5.124	-.049	3.889	1.144	22.913	35.430	-12.512
	(4.529)	(.209)	(4.027)	(1.171)	(68.949)	(49.942)	(29.143)
C.Financial incentive 2							
High Environmental Motivation	-12.878	.235	2.790	.405	215.337	40.572	174.800*
	(9.814)	(.482)	(14.734)	(4.161)	(216.915)	(160.051)	(93.394)
Low Environmental Motivation	-2.710	.458*	8.268	2.496	121.896	100.856	21.076
	(4.310)	(.268)	(6.231)	(1.830)	(100.291)	(74.163)	(41.467)

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 environmental motivation. Environmental motivations are determined from the enrollment survey question about motivations for charging on campus. Low (high) motivation indicates a reponse of <20 points (>20 points) allocated to the answer "I prefer to charge when and where I think the environmental impact will be the lowest". 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 charging behavior by vehicle type

	Total charging behavior						
	(1) Share	(2) Sessions	(3) Energy	(4) Cost	(5) Duration	(6) Charge Time	(7) Idle Time
A.Informational prompt							
Battery Electric	3.262	.008	-3.097	-.966	-87.401	-36.165	-51.261
	(4.292)	(.298)	(6.817)	(1.882)	(112.903)	(83.254)	(45.122)
Plug-in Hybrid	-11.236	-.225	-3.841	-1.244	-31.729	-63.114	31.415
	(8.752)	(.694)	(6.243)	(1.790)	(203.376)	(98.546)	(129.112)
B.Financial incentive 1							
Battery Electric	-2.061	-.060	6.056	1.757	35.009	43.373	-8.369
	(4.811)	(.223)	(4.879)	(1.415)	(76.848)	(58.279)	(27.611)
Plug-in Hybrid	-11.921	.195	2.947	.795	73.588	78.051	-4.429
	(11.254)	(.515)	(4.934)	(1.430)	(154.505)	(72.793)	(100.893)
C.Financial incentive 2							
Battery Electric	-4.338	.501*	10.949	3.224	169.378	128.795	40.608
	(4.832)	(.265)	(7.258)	(2.130)	(105.770)	(83.108)	(37.315)
Plug-in Hybrid	-2.732	.217	-2.927	-.817	10.552	-17.246	27.869
	(9.327)	(.597)	(5.892)	(1.725)	(169.501)	(91.534)	(102.981)

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.

D.3 Effect on the timing of charging behavior

Table D11: 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	-.005	-.056	.107	.042	.025
	(.011)	(.053)	(.128)	(.032)	(.031)
ChargePoint	-.043	-.077	.051	-.076	-.014
	(.045)	(.064)	(.127)	(.136)	(.077)
B.Financial incentive 1					
PowerFlex	-.001	.037	-.014	.007	-.001
	(.012)	(.031)	(.086)	(.022)	(.018)
ChargePoint	.073**	.036	-.055	-.052	-.036
	(.031)	(.031)	(.101)	(.102)	(.060)
C.Financial incentive 2					
PowerFlex	.004	-.052	.100	.034	.038
	(.010)	(.061)	(.085)	(.030)	(.031)
ChargePoint	.047	-.008	-.050	.191	.191**
	(.067)	(.054)	(.110)	(.129)	(.091)
D.Interaction					
PowerFlex	-.000	-.039	.054	.033	.028
	(.019)	(.073)	(.229)	(.053)	(.051)
ChargePoint	-.070	-.108	.082	.024	-.023
	(.077)	(.078)	(.249)	(.217)	(.133)

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 D12: Effect on the timing of charging by commute distance

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Short Commute	-.065	-.170**	-.025	-.083	-.077
	(.048)	(.074)	(.203)	(.201)	(.126)
Medium Commute	-.014	-.085	.037	.007	-.011
	(.056)	(.114)	(.219)	(.174)	(.099)
Long Commute	-.071	-.150	.455	-.034	.114
	(.073)	(.111)	(.299)	(.212)	(.143)
B.Financial incentive 1					
Short Commute	.055	.026	-.111	-.078	-.049
	(.058)	(.046)	(.155)	(.132)	(.085)
Medium Commute	.068	.062	-.089	-.014	.022
	(.051)	(.056)	(.164)	(.144)	(.095)
Long Commute	.093**	.130*	-.007	-.043	-.081
	(.044)	(.074)	(.176)	(.136)	(.095)
C.Financial incentive 2					
Short Commute	.170	-.098	.001	.234	.364**
	(.174)	(.081)	(.162)	(.165)	(.145)
Medium Commute	.041	-.091	.039	.367*	.289*
	(.053)	(.091)	(.182)	(.211)	(.152)
Long Commute	-.048	.004	.106	.074	.043
	(.066)	(.143)	(.214)	(.215)	(.160)

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. A short commute is <7.5 miles, one-way; medium commute, <7.5 and >15 miles; and long commute, >15 miles. 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 D13: 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	.031	-.091	-.097	.219	.033
	(.064)	(.081)	(.195)	(.173)	(.124)
Frequent Commute	-.086	-.152	.279	-.154	.001
	(.066)	(.097)	(.215)	(.182)	(.108)
B.Financial incentive 1					
Infrequent Commute	.005	-.007	-.126	.042	-.106
	(.046)	(.046)	(.149)	(.132)	(.077)
Frequent Commute	.107**	.114*	-.039	-.091	-.001
	(.044)	(.058)	(.155)	(.131)	(.086)
C.Financial incentive 2					
Infrequent Commute	-.073	-.103	.075	.243	.032
	(.071)	(.076)	(.165)	(.167)	(.140)
Frequent Commute	.112	-.040	.038	.217	.324***
	(.100)	(.106)	(.164)	(.169)	(.118)

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 D14: Effect on the timing of charging by affiliation

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Student	-.056	-.157**	.108	.230	.140
	(.058)	(.077)	(.257)	(.280)	(.200)
Faculty	.046	-.146	-.684***	-.230	-.112
	(.063)	(.103)	(.230)	(.213)	(.093)
Staff	-.073	-.103	.447*	-.122	-.001
	(.050)	(.115)	(.233)	(.168)	(.095)
B.Financial incentive 1					
Student	.087	-.022	-.196	.110	.114
	(.068)	(.043)	(.161)	(.174)	(.126)
Faculty	-.009	.025	-.398**	-.242*	-.117
	(.040)	(.066)	(.195)	(.140)	(.089)
Staff	.087*	.098	.070	-.049	-.088
	(.048)	(.063)	(.155)	(.117)	(.072)
C.Financial incentive 2					
Student	.208	-.161**	-.168	.374	.528**
	(.198)	(.070)	(.178)	(.264)	(.231)
Faculty	-.025	.011	.142	.467*	-.035
	(.046)	(.103)	(.270)	(.262)	(.107)
Staff	-.012	-.013	.119	.075	.165
	(.042)	(.120)	(.166)	(.140)	(.112)

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 affiliation. 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 income

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
Low Income	-.027	-.084	.030	-.324	-.320
	(.075)	(.089)	(.247)	(.266)	(.209)
Medium Income	-.047	.016	.451	-.055	-.002
	(.047)	(.133)	(.314)	(.218)	(.124)
High Income	-.065	-.263**	.058	.185	.254**
	(.100)	(.113)	(.251)	(.180)	(.124)
B.Financial incentive 1					
Low Income	.141**	.051	.025	.038	.053
	(.069)	(.048)	(.188)	(.192)	(.116)
Medium Income	-.045	.052	.118	-.098	-.116
	(.028)	(.072)	(.177)	(.141)	(.099)
High Income	.096	.104	-.272	-.077	-.055
	(.059)	(.072)	(.193)	(.132)	(.102)
C.Financial incentive 2					
Low Income	.176	-.030	.105	.298	.382**
	(.190)	(.096)	(.209)	(.258)	(.189)
Medium Income	-.027	-.084	.242	.303	-.026
	(.056)	(.139)	(.217)	(.221)	(.126)
High Income	.005	-.069	-.115	.121	.274**
	(.043)	(.107)	(.187)	(.155)	(.131)

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 affiliation. Low income refers to less than $100k, medium income $100-$200k, and high income above $200k. 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), mid-day (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 D16: 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	-.111	-.122	.175	-.058	-.055
	(.079)	(.107)	(.237)	(.177)	(.093)
No Home Charger	.046	-.149	.132	.003	.111
	(.052)	(.105)	(.248)	(.235)	(.178)
B.Financial incentive 1					
Home Charger	.055	.067	.009	.041	-.072
	(.048)	(.060)	(.157)	(.121)	(.073)
No Home Charger	.096*	.081	-.177	-.166	.012
	(.049)	(.059)	(.204)	(.195)	(.134)
C.Financial incentive 1					
Home Charger	.086	-.016	.001	.136	.100
	(.102)	(.100)	(.157)	(.139)	(.085)
No Home Charger	.001	-.127	.121	.357	.418**
	(.065)	(.104)	(.205)	(.246)	(.188)

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 D17: 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	-.033	-.024	-.189	.073	-.198*
	(.052)	(.107)	(.214)	(.203)	(.117)
Medium Charge Rate	-.067	-.099	.181	-.017	-.014
	(.055)	(.093)	(.211)	(.175)	(.091)
High Charge Rate	-.010	-.332**	.430	-.185	.283
	(.077)	(.136)	(.304)	(.248)	(.202)
B.Financial incentive 1					
Low Charge Rate	.001	.062	-.247	-.227*	-.177*
	(.035)	(.072)	(.202)	(.118)	(.092)
Medium Charge Rate	.053	.070	-.024	.024	-.017
	(.041)	(.048)	(.140)	(.126)	(.077)
High Charge Rate	.214**	.095	-.014	-.065	.058
	(.095)	(.134)	(.216)	(.170)	(.124)
C.Financial incentive 2					
Low Charge Rate	-.040	-.022	-.028	.073	.011
	(.037)	(.115)	(.170)	(.166)	(.073)
Medium Charge Rate	.096	-.105	.025	.358*	.223*
	(.104)	(.081)	(.163)	(.184)	(.133)
High Charge Rate	.021	.033	.225	-.010	.512**
	(.070)	(.231)	(.263)	(.195)	(.245)

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.

Table D18: Effect on the timing of charging by environmental motivation

	Timing of initiated charging session				
	(1) 21-5	(2) 5-7	(3) 7-10	(4) 10-16	(5) 16-21
A.Informational prompt					
High Environmental Motivation	-.006	-.118	.287	-.284	.196
	(.085)	(.115)	(.334)	(.259)	(.296)
Low Environmental Motivation	-.053	-.134	.143	-.005	-.011
	(.047)	(.083)	(.182)	(.147)	(.081)
B.Financial incentive 1					
High Environmental Motivation	.058	.053	.251	.128	-.040
	(.058)	(.071)	(.292)	(.294)	(.114)
Low Environmental Motivation	.073**	.075*	-.099	-.062	-.036
	(.036)	(.043)	(.126)	(.106)	(.065)
C.Financial incentive 2					
High Environmental Motivation	.004	-.082	.151	-.011	.155
	(.080)	(.176)	(.270)	(.294)	(.169)
Low Environmental Motivation	.057	-.058	.038	.254*	.238**
	(.075)	(.082)	(.141)	(.144)	(.101)

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 environmental motivation. Environmental motivations are determined from the enrollment survey question about motivations for charging on campus. Low (high) motivation indicates a reponse of <20 points (>20 points) allocated to the answer "I prefer to charge when and where I think the environmental impact will be the lowest". 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 D19: Effect on the timing of charging by vehicle type

	Outcome Variable				
	(1) 0-4	(2) 5-6	(3) 7-9	(4) 10-12	(5) 12-16
A.Informational prompt					
Battery Electric	-.001	-.117	.127	-.051	.050
	(.036)	(.091)	(.174)	(.161)	(.095)
Plug-in Hybrid	-.203	-.184	.259	.021	-.118
	(.166)	(.152)	(.424)	(.322)	(.254)
B.Financial incentive 1					
Battery Electric	.078**	.086*	-.153	-.059	-.012
	(.038)	(.046)	(.140)	(.118)	(.066)
Plug-in Hybrid	.051	.022	.245	.004	-.128
	(.073)	(.115)	(.271)	(.234)	(.186)
C.Financial incentive 2					
Battery Electric	.093	-.008	.001	.230	.251**
	(.082)	(.092)	(.138)	(.147)	(.098)
Plug-in Hybrid	-.083	-.231*	.208	.211	.158
	(.098)	(.124)	(.321)	(.288)	(.228)

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), mid-day (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.

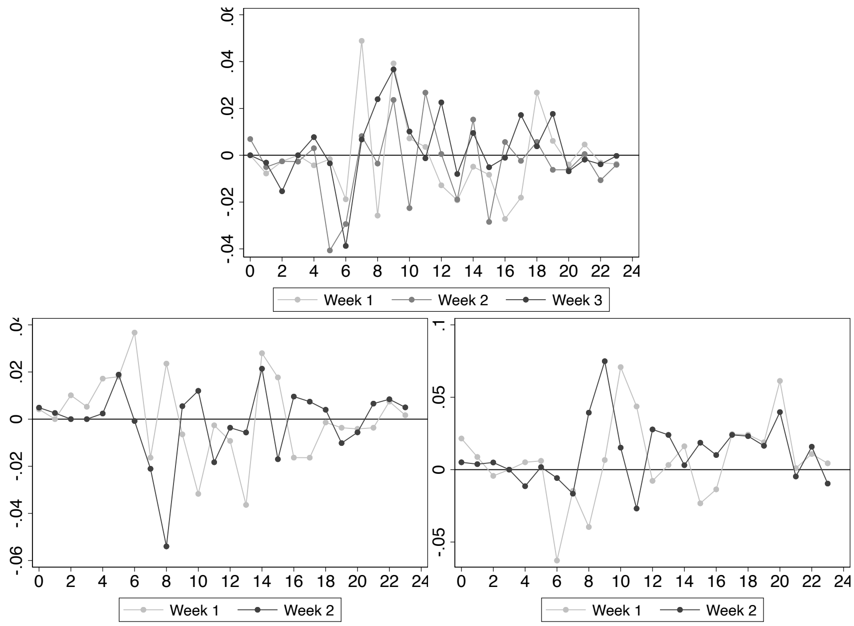


Figure D1: Effect on hourly charging sessions by week

Notes: The figure displays the regression coefficients of the informational, first financial, and second financial treatment on hourly energy consumption (kWh) by week. The outcome variable indicates the total number of charging sessions in the indicated time interval.

E 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. This section presents the experimental schedule (Section E.1), descriptive statistics (Section E.2), and empirical results (Section E.3) of the trial experiment.

E.1 Experimental schedule

The experimental schedule of the spring trial experiment is documented in Figure E1. 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.

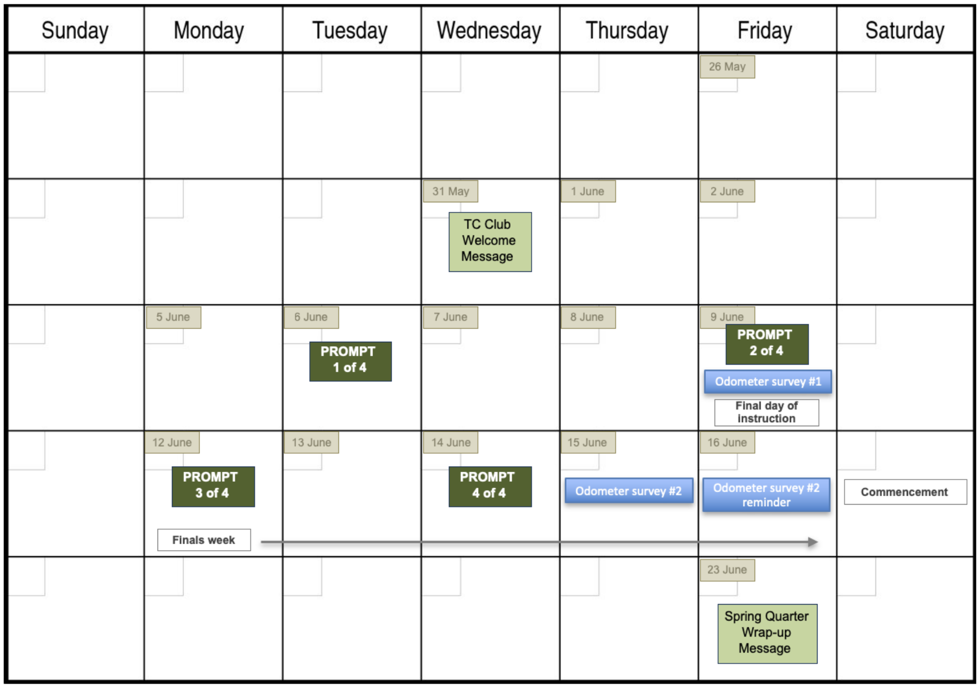


Figure E1: Experimental schedule for the spring trial experiment

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.

E.2 Descriptive statistics

Table E1: Participant characteristics and charging behavior for the spring trial experiment

	Mean	Std. dev.	Min	Max	Obs.
A.Socio Demographic Variables					
Age	38.00	12.95	22	80	419
Share Male (in %)	0.51	0.50	0	1	419
Income ('000)	143.24	64.60	25	200	333
Years of Education	17.02	3.03	11	21	419
Days on Campus	3.29	1.68	0	6	419
B.Vehicle Attributes					
Vehicle Age	2.59	2.60	0	22	419
Battery Electric (in %)	0.76	0.43	0	1	419
Odometer Reading	26197.98	24283.40	188	149,320	227
Daily Mileage	49.57	53.89	0	333	88
C.Charging Characteristics					
Home Charger (in %)	0.61	0.49	0	1	419
Charging Price (cents per kWh)	0.19	0.12	0	1	272
Charging Club Member (in %)	0.34	0.47	0	1	419
D.Outcome Variables					
Average Session (in min)	307.42	196.14	1	902	208
Average Charging (in min)	206.20	142.10	0	750	208
Average Idle Time (in min)	101.22	144.06	0	735	208
Average Energy (in kWh)	18.10	13.67	0	66	208
Average Price	3.79	2.96	0	20	208
Number of Charging Session	1.73	2.52	0	18	419
Share Campus	0.26	0.34	0	1	73

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; the outcome variables (Panel D), which characterize charging behavior, include all charging sessions between June 6 and June 16.

E.3 Empirical results

To estimate the effect of the informational treatment on campus charging behavior, we run the following regression:

$$y_i \;=\; \beta Treatment_i \;+\; \gamma X_i \;+\; \alpha_i \;+ \varepsilon_{it}, \tag{1}$$

where i indexes the individual; y_i refers to the relevant outcome of interest; $Treatment_i$ is a dummy variable equal to 1 if the individual received the informational prompts; the vector X_i represents a rich set of individual socio-demographic variables, vehicle characteristics, charging attributes, and motivation about charging; and α_j are vehicle fixed effects to control for time-invariant vehicle characteristics.

The primary outcome variable of interest is the share of total charging done on campus, on an energy basis. In addition, we analyze the number of campus charging sessions, total energy consumed, session cost, session duration, charging duration, and idle duration.

Table E2: 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.

F Policy implication

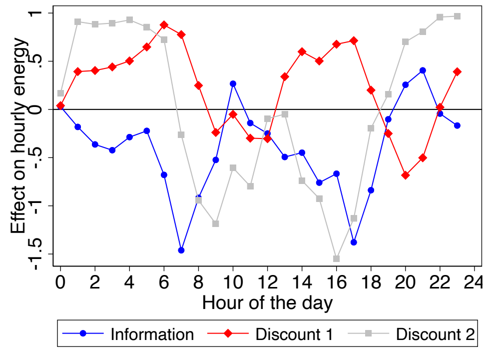


Figure F1: Effect on hourly charging sessions

Notes: The figure displays the regression coefficients of the informational, first financial, and second financial treatment on hourly energy consumption (kWh). The outcome variable indicates the total number of charging sessions in the indicated time interval.

References

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