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

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Abstract

Synchronizing electric vehicle (EV) charging with periods of abundant renewable energy is essential for decarbonizing transportation. In solar-dominated grids, this requires shifting charging to midday hours–typically when vehicles are parked at workplaces. Yet workplace charging networks operate under institutional constraints such as shared infrastructure, bundled parking and charging, and limited willingness to require drivers to move vehicles making time-of-day pricing and active management difficult to implement. In a natural field experiment (n = 629 drivers) across a large workplace charging network, we randomize time-invariant price discounts and environmental information emphasizing the benefits of daytime charging. Price discounts modestly increase workplace charging but shift charging toward off-solar periods when network utilization is lower, while environmental nudges re-time charging toward solar hours without increasing total demand. A follow-up experiment and heterogeneity analyses show that these timing responses are driven by perceived charger scarcity and congestion under price discounts. Finally, we quantify the abatement costs per ton of CO_2 of these shifts.

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I. Introduction

Every credible plan for deep reductions in greenhouse gas emissions necessary to avoid catastrophic climate change includes the widespread electrification of light-duty transportation (International Energy Agency, 2021).[1] However, the realized environmental benefits of electric vehicles (EVs) depend not only on what people drive, but also on *when* they charge. In grids with high solar penetration, marginal emissions are typically lowest during late morning and midday when solar output is abundant, and higher in the evening and overnight when fossil generation is more likely to set the margin (Imelda et al., 2022). Beyond emissions, shifting EV charging toward midday hours can reduce renewable curtailment, ease net-load ramping and generator startup costs, and contribute to resource adequacy by increasing demand during periods of low net load.[2] These patterns have motivated growing interest in shifting EV charging toward daytime hours with a natural focus on workplaces, where vehicles are often parked for extended periods during the day. Indeed, as EV adoption expands beyond early adopters—many of whom have access to home charging (LaMonaca & Ryan, 2022)—workplace and other shared charging environments will become increasingly important for both charging access (Chakraborty et al., 2019) and grid management.

In this paper, we conduct a natural field experiment ($n = 629$) amongst the near universe of EV chargers in a large workplace to evaluate financial and informational interventions to increase workplace daytime EV charging. Our interventions include (i) financial discounts invariant to the time of day for charging at work and (ii) environmental nudges, which provide information on the benefits of daytime charging. Importantly, because employers can increase the convenience and affordability of driving electric for their employees by providing workplace charging, our financial incentives were not time specific. This design choice reflects both the desire to avoid disruptions from employees moving vehicles during the day and the fact that cars are typically parked for the full workday, making non-time-specific incentives a more practical and institutionally compatible approach (US Department of Energy, 2022).

[1] In the three largest markets (China, E.U., and the U.S.), electric vehicles (EVs) currently make up 10–38% of passenger vehicle sales. These jurisdictions have each set ambitious targets of 50-100% EV sales by 2030–2035 (European Environment Agency, 2021; Office of the Press Secretary, 2021; Executive Department State of California, 2020).

[2] As the electric grid incorporates more intermittent renewable sources, the value of flexible demand – like workplace EV charging – rises in importance for balancing supply and demand (Holland et al., 2022; Powell et al., 2022). For example, in California—where solar generation is abundant during midday hours—renewable curtailment has become common. Between December 2022 and November 2023, the California Independent System Operator curtailed approximately 2.6 million MWh of renewable electricity, largely during periods of high solar output (California Independent System Operator, 2024). Shifting flexible demand such as EV charging into these hours can help absorb excess generation and mitigate evening ramping pressures, although the magnitude of these effects depends on adoption and system conditions.

We study time-invariant workplace charging incentives for three reasons. First, unlike residential charging, workplace charging operates under binding institutional constraints: charging capacity is scarce, chargers are bundled with parking stalls, and employers are generally unwilling to ask workers to interrupt the workday to move vehicles in response to time-limited or time-varying incentives (US Department of Energy, 2022) and instead rely on second best tools like flat discounts (Asensio et al., 2022). As a result, time-of-day pricing—while effective in residential settings (Bailey et al., 2025; Bernard et al., 2025; La Nauze et al., 2024)—is often impractical in workplace environments. Second, flat incentives are not behaviorally neutral in shared and congested charging networks. By interacting with limited capacity, heterogeneous reliability, and uncertain access, time-invariant discounts can affect not only how much drivers charge at work but also when they arrive and plug in, potentially inducing strategic responses driven by perceived scarcity. Third, although managed and automated charging technologies can technically align charging more closely with marginal pricing (McClone et al., 2023), their effectiveness depends on drivers first being plugged in for non-trivial extended and predictable time periods (Metcalfe et al., 2026). Time-invariant incentives therefore operate on the critical upstream margin encouraging workplace charging participation while also shaping the congestion and timing environment in which future managed charging systems will operate.

We implement the experiment at the University of California San Diego (UCSD), which hosts one of the largest workplace EV charging networks in the region. The campus infrastructure reflects a common model in professional workplaces, where parking spots are selectively equipped with chargers due to cost constraints and rapid technological change. As a result, the network has typical features for such workplaces such as shared infrastructure, multiple parking facilities and substantial daily congestion. Two features of our setting are particularly valuable to our research design. First, we observe the near universe of those who utilize the charging network on campus. Second, although multiple privately operated charging networks are present on campus, we observe the complete on-campus charging activity of each individual in our study. With the cooperation of the transportation office, we facilitated consent and data integration by creating a dedicated EV charging club that contains the near-universe of campus affiliates who utilize the network, allowing us to link detailed charging-session data to individual drivers across networks.

Our experiment investigates how environmental nudges and financial incentives can induce a shift in *where* and *when* drivers charge. It consists of two interventions implemented sequentially: an informational treatment from October 5 to 23, 2023, followed by two phases of financial treatment from October 24 to November 19. In the informational intervention, drivers receive emails highlighting the CO_2 emission benefits of daytime versus nighttime charging, delivered three times (once per week) over the treatment period. In the financial intervention, drivers receive discounts on workplace charging that are invariant to the time of day. In the first financial phase, participants are assigned to either a small (\$.16/kWh) or large (\$.23/kWh) discount off the base workplace price of \$.30/kWh, making workplace charging slightly cheaper than overnight home charging or equal to the average locational marginal price of electricity, respectively.[3] In the second phase, half of the large-discount group is reassigned to the small discount while the remainder continues to receive the large discount, allowing us to examine the persistence of workplace charging behavior when incentives are reduced.

Our results show that workplace charging demand is only modestly price responsive in this congested, shared-infrastructure setting. We find that even substantial financial incentives produce only modest changes in workplace charging behavior. Moving from the small to the large workplace discount (a 50% price reduction) increases workplace energy consumption by 23%, implying a price elasticity of workplace charging of $-.46$. To put this into context, the estimated off-peak price elasticity of EV charging is -1.59 in response to a 23% overnight price reduction (Bailey et al., 2025), while Bernard et al. (2025) report elasticities of -1.45 and -1 for users that did not switch from other apps following 40% and 15% price cuts, respectively. This low responsiveness suggests that in congested, variable-quality workplace networks, location-specific discounts alone are insufficient to induce large-scale substitution toward daytime workplace charging.

In contrast to the modest effects on total energy, our interventions meaningfully shift *when* charging occurs at work. Environmental information reduces early-morning charging by 0.041 sessions per driver-week (5.3%) and shifts initiation to later-morning hours, moving charging modestly toward solar-aligned periods. Price discounts shift timing in the opposite direction: the first discount phase increases early-morning charging by 0.042 sessions per driver-week (4.9%) and overnight charging by 0.029 (3.3%), and the second phase increases evening sessions by 0.112 (12.9%).

This unintended timing response points to a central mechanism in workplace charging: when parking stalls are bundled with chargers and capacity is scarce, price incentives may alter drivers' *perceptions* of access rather than their valuation of electricity (Badia et al., 2019). To test this hypothesis directly, we conduct a second experiment that holds financial incentives constant while experimentally varying beliefs about how many drivers receive the discount. Drivers primed to perceive high incentive-induced scarcity shifted from early morning to evening when the network is less utilized, highlighting that perceptions

[3]Throughout the paper, we refer to the effect of financial incentives as the difference between the large and small discount groups.

of scarcity alone shift charging behavior toward periods of lower utilization. Furthermore, drivers who predominantly charge in parking garages with high utilization of chargers during the morning commute period shift to off-peak periods to ensure they receive a charge. Drivers who shift when they charge during the discounts are those who charge predominantly in parking garages with reliable chargers (i.e., with high rates of sessions that supply meaningful energy). This suggests that financial incentives have stronger temporal effects when drivers expect charging facilities to deliver a meaningful charge. Finally, drivers' responses to the interventions vary with socio-demographic and commuting characteristics: frequent commuters with flexible schedules, as well as those without home chargers or facing high charging costs, are more likely to shift charging to evening and overnight periods in response to financial incentives.

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 to design policies to shape these decisions. This paper advances the state of research along all three lines. First, because early adopters of EVs tend to be wealthier and have higher homeownership rates (Davis, 2019), studies consistently show that the majority of charging occurs overnight (Helmus et al., 2020) at home (Lee et al., 2020). As the profile of EV buyers shifts to adopters who are less wealthy and less likely to own a home, there is a growing recognition that workplace charging will play a crucial role in both fostering EV adoption (Dorsey et al., 2024) and meeting the growing demand for charging (Tal et al., 2020). Yet, to our knowledge, there exists no experimental evidence on how to induce a shift to daytime workplace charging.[4] Our workplace-wide experiment marks the first effort to deliver evidence on micro-level charging behavior at the workplace and constitutes the largest experimental study for workplace EV research.[5]

Second, the identified clusters of mechanisms contribute to our understanding of why drivers shift the timing of their workplace charges. We establish network congestion – i.e., when the number of EV drivers who wish to charge exceeds available chargers – as a central

[4]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), prizes and auctions (Fetene et al., 2017), financial penalties (Asensio et al., 2021), and financial discounts (Bailey et al., 2025). 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).

[5]Although the literature lacks an experimental basis around workplace EV charging, there are ongoing studies that study how to develop systems for smart EV charging to reduce the impact on the power grid. These include studies at the Cadarache research center near Aix-en-Provence (Robisson et al., 2022), the University Campus Lyngby in Denmark (Askjær et al., 2020), the project ChargeForward in the San Francisco Bay area (Lipman et al., 2020), and the Dutch INVADE pilot (2024).

impediment to shifting drivers to daytime workplace charging.[6] Our work highlights how financial incentives can backfire when they induce a perceived scarcity of chargers in a congested network. When parking and charging capacity is limited, as is common in most workplaces around the world, the scarcity concerns from discounted prices to charge at work can cause unintended shifts to evening charging with higher grid intensity.[7]

Third, our empirical findings can inform charging strategies intended to align charging behavior with policy objectives. While there is little evidentiary basis for how these policies affect the efficiency of the workplace network,[8] we derive an empirical framework that allows us to estimate the emission damages from the effect of our interventions. Our framework characterizes how shifts in the workplace charging usage and timing alter CO_2 emissions. Finally, we also derive the financial implications from LCFS revenues for the workplace that hosts the charging network and the local utility company.

The rest of the paper proceeds as follows. Section II presents the experimental design and data. Section III provides the methodology, findings, and mechanisms. Section IV discusses the environmental implications. Section V concludes with policy implications.

II. Experiment

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

We conducted the field experiment at UCSD, which operates one of the world's largest EV charging networks in a single workplace. We coordinate closely with campus administrators (UCSD's Transportation Services) responsible for workplace charging policy and pricing as well as two leading charging vendors, ChargePoint and PowerFlex, which collect and share charge session data. To recruit research participants, we created a campus club for

[6]This aligns with the literature that identifies charger scarcity as a major barrier to widespread EV adoption (Tal et al., 2014; Bornioli et al., 2023) and influence on 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).

[7]This relates to a literature on the unintended consequences of environmental policies that have been established in the context of daylight saving time (Kotchen & Grant, 2011), marginal emissions from charging electric cars (Zivin et al., 2014), and building codes (Levinson, 2016).

[8]Institutions have implemented numerous practices 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). Research has found that these policies can inhibit workplace charging as much as they encourage it (Caperello et al., 2013), e.g., by causing rather than alleviating congestion (Nicholas & Tal, 2015).

EV drivers – the "Triton Chargers" – open to UCSD affiliates (students, staff, and faculty), in which drivers opt-in, consent to research, and receive discounts for charging at work and opportunities to win raffle prizes (monthly $50 gift cards for being a member and larger quarterly gift cards for responding to surveys).[9] 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' workplace charging activity and analyze potential behavioral shifts in response to interventions. Appendix A.1 describes the recruitment of EV drivers at UCSD.

A. Design of informational and financial interventions

The experiment consists of two interventions run in series – an informational treatment run over 19 days from October 5–23, followed by two phases of financial treatment run over 27 days from October 24 to November 19 (Figure 1). Interventions were conducted within one academic quarter to maintain consistency in workplace population and schedules.

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.2 reports the email message and calculations for these quantities.

[9]Participants were recruited through university-wide email campaigns and posting flyers on EVs parked at UCSD. During recruitment, drivers were told that by participating in the study, they can receive information about campus charging and the offer of discounted charging. The Triton Chargers and associated experimental social science research at UCSD are part of a broader research testbed for distributed energy, called "DERConnect," which is open to outside researchers.

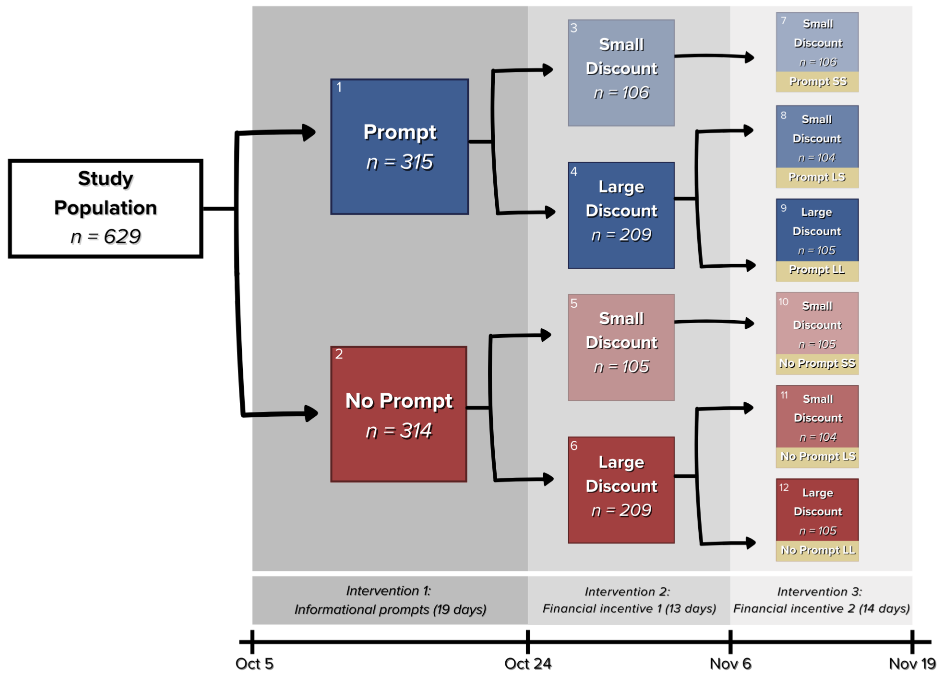

Figure 1: Experimental design

Notes: This figure shows participant assignment to treatment and control groups over the three phases of our experiment: informational (Oct 5-23), first financial (Oct 24-Nov 5), and second financial (Nov 6-19). Figure A2 documents the full experimental schedule.

In the financial intervention, all drivers received discounts for Level-2 charging and were randomly placed into treatment arms that varied discount size.[10] The financial intervention consists of two phases. 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 workplace rate of $\$.30/kWh$, respectively.[11] Our design compares large versus small discounts, rather than including a pure control group without financial incentives. This ensures that both groups are equally aware of their participation in the experiment, allowing us to identify the causal effect of price changes rather than potential experimenter demand effects (De Quidt et al., 2018). 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 any

[10] The vast majority of UCSD chargers are Level-2. Participants report rarely using the small number of DC Fast chargers at work and we exclude these from this study.

[11] One drawback to our design is that we lack direct access to the prices charged by (and displayed at) charging stations. Drivers pay full price for their charging activity 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).

economic advantage of overnight home charging. While SDG&E's rates vary by hour and are cheapest overnight (Table B1), workplace rates and discounts apply equally to all hours of the day. The large-discount rate of $\$.07/kWh$ is equivalent to the mean LMP of wholesale electricity at UCSD, corresponding to the plausible lowest cost that drivers could pay for charging. Appendix A.3 summarizes the prompts for the financial discounts.

During the second phase (November 6–19; 14 days), half of the large discount group continues with the large discount, while the other half moves to the small discount.[12] 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 during the first discount.

Appendix A.4 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).

B. Key datasets

1. *Charging network data.* During our experiment, the UCSD charging network comprised 331 Level-2 charging ports, including 250 ChargePoint and 72 PowerFlex stations.[13] 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.[14] They also record the unique (anonymized) ID of the driver who initiated the session, allowing us to link drivers to charging sessions. We exclude sessions that indicate an initiation error (i.e., that consume less than .5 kWh or last fewer than 5 minutes) or flout

[12] To ensure parity in the number of active work days across both financial treatments, we schedule the second treatment to span 14 days, accounting for Veterans Day on November 10 when commuters are likely absent from work.

[13] UCSD plans to install an additional 760 Level-2 and 35 DC Fast Charger stations by the end of 2025. We exclude eight Level-2 chargers operated by SemaConnect.

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

parking rules (i.e., exceed 16 hours).[15] Appendix B.1 provides information on chargers and parking rules at UCSD.

2. *Driver data.* Upon enrolling in the Triton Chargers EV club, drivers provide information on their demographics (age, gender, income, and education), university affiliation, vehicle (year, make, model, type), living arrangement (rent or own, dwelling type), charging behaviors (access to charging alternatives, fraction of charging done by location), commuting behavior (commute frequency and distance, obtained via zip code),[16] and motivation for choosing workplace charging locations (Table 1, A–C). In addition, we periodically request odometer readings to track total driving before, during, and after interventions. Throughout our experiment, Triton Chargers accounted for approximately 36% and 27% of the energy consumed at PowerFlex and ChargePoint stations at UCSD, respectively.

3. *Other data.* In addition to workplace charging, drivers may 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 LMP 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 depend on the carbon intensity of electricity, we use emission factors published by the California Air Resources Board (2023).

C. Descriptive statistics

Table 1 summarizes participants' demographics (Panel A), vehicle attributes (Panel B), and commuting and charging habits (Panel C), along with the outcome variables that characterize 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 work. Participants are mostly staff (49%), faculty (21%), or graduate students (18%) and either own a single-family house (43%) or rent off-campus (34%).[17] 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 36 miles,

[15] Campus rules permit 4 hours of charging at ChargePoint stations and 12 hours at PowerFlex stations. Although the maximum allowable duration is 12 hours, we include a small subset lasting 12 to 16 hours. We show that the effect on the timing of charging behavior remains consistent even when including charging sessions with initiation errors (Table C1).

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

[17] 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.

Table 1: 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 ($1,000s)	135.73	66.58	25	200	557
Years of education	17.18	3.09	11	21	629
B.Vehicle attributes					
Vehicle age (years)	2.38	2.59	0	22	629
Battery electric (%)	0.76	0.43	0	1	629
Odometer reading (miles)	31078	29395	28	205,573	444
C.Commuting and charging habits					
Days at work per week	3.26	1.75	0	6	629
Daily mileage (miles)	36.31	29.09	0	312	357
Home charger (%)	0.59	0.49	0	1	629
Charging price ($ per kWh)	0.18	0.12	0	1	382
D.Outcome variables					
Share of energy at work (%)	31.61	34.63	0	100	351
Weekly charging sessions	0.88	1.19	0	9	629
Energy consumed (kWh)	18.89	12.23	1	67	403
Session duration (min)	318	172	9	792	403
Charging duration (min)	233	137	9	749	403
Idle duration (min)	85	104	0	614	403

Notes: This table reports descriptive statistics on driver demographics (Panel A), vehicle attributes (Panel B), commuting and charging habits (Panel C), and outcome variables of interest (Panel D) for experiment participants. Driver data (Panel A-C) are from the Triton Chargers EV club enrollment survey prior to the experiment; the outcome variables (Panel D), which characterize charging behavior, include all charging sessions between the first informational prompt (October 5) and the conclusion of the financial treatment (November 19). We report averages for age, income, and education, while our survey asked respondents to select the appropriate bracket for each.

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, although 190 participants (30% of the sample) report not knowing the price they typically pay to charge.

Per vendor charging session data, drivers initiated .89 weekly workplace charging sessions during the experiment. The mean session, charging, and idle durations were 318, 233, and 85 minutes, respectively. The average energy consumed was 19 kWh, and participants did 30% of their charging at work (on an energy basis). During our experiment, 403 out of 629 participants initiated at least one workplace charging session. Figure A3 displays charging behavior patterns based on location, time of day, reasons for charging, and motivation to charge at work. Drivers self-report that they charge mostly at work or at home while also utilizing other locations such as charging plazas and destination charging. Drivers self-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 at work, where prices are the same everywhere, they report choosing charging locations nearest their office (39%) or where they think they are most likely to find an open charger (31%).

III. Empirical results

A. Methodology

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

$$y_{iw} = \beta Info_i + \delta_1 Reward_{1i} + \eta(Info_i \cdot Reward_{1i}) + \gamma X_i + \alpha_j + \omega_w + \varepsilon_{iw}, \quad (1)$$

where i and w index the driver and the week; y_{iw} refers to the weekly 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;[18] and α_j and ω_w are garage-fixed effects (i.e., modal charging location) and week-fixed effects to control for time-invariant charging characteristics and campus-wide temporal trends.[19]

[18]Socio-demographic control variables include age, gender, income, years of education, weekly days commuting to work, and commuting distance. Vehicle characteristics and charging attributes include battery size, energy efficiency, vehicle type, odometer reading, an indicator for access to home charging, and charging price. As some respondents did not state their income and charging price, we use the average as a proxy for this variable. 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 at work.

[19]We also document that the estimated coefficients are robust to including vehicle-brand-fixed effects in

The coefficients of interest β and δ_1 measure the effect of the information and the first financial treatment on the outcome of interest. The coefficient η measures the interaction effect between informational and financial treatment. Standard errors are clustered at the individual-level.

For the second phase of the financial experiment, we estimate a specification analogous to equation (1), replacing the indicator variable $Reward_{1i}$ with $Reward_{2i}$, which equals one if individual i was assigned to the large discount group in the second phase. To estimate habit formation, we restrict the sample to drivers who received the first financial incentive and compare the charging behavior of those who continued to receive large discounts with those who were assigned to smaller discounts. We run the following equation (2) to estimate the effect of the second financial treatment:

$$y_{iw} = \delta_2 \, Reward_{2i} + \phi \, Info_i + \gamma X_i + \alpha_j + \ \omega_w \ + \varepsilon_{iw}. \tag{2}$$

We additionally control for the total energy and charging sessions during the five distinct time periods on Veterans Day (November 10), as well as whether the individual received the informational prompts during the first phase of the experiment. The coefficient δ_2 measures the effect of the second financial treatment on the outcome of interest.

We use the model specifications in equation (1) and (2) to analyze total workplace charging activity and the timing of workplace charging. To measure changes in total charging, we analyze six outcome variables: each driver's share of charging done at work, the number of sessions initiated, energy consumed, session duration, charging duration, and idle duration (Panel D, Table 1). A driver's share of charging at work is the total energy consumed from workplace 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.[20]

To measure the effect of interventions on the timing of charging (measured by the hour in which sessions are initiated), we analyze charging over five distinct periods: early morning (5:00–6:59), which sees the earliest morning commuters arrive 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, along with rising solar production; midday (10:00–15:59), characterized by relatively constant high utilization and maximal solar generation; evening (16:00–20:59), characterized by departing commuters, arrival of nighttime workers, and rapidly waning solar generation; and overnight (21:00–4:59), characterized by

addition to the vehicle characteristics and garage-fixed effects (Table C2).

[20]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).

low network utilization. Californians are incentivized through time-of-use pricing to avoid using electricity during the evening period.

To assess the quality of our three randomizations, we compare mean values and provide balance tests on driver demographics, vehicle attributes, and commuting and charging habits in Table A1. Using a two-way t-test, the table shows that the randomization achieved balance across the observed covariates for the treated and control groups during each intervention. The only statistically significant difference when comparing mean values is the share of male commuters for the informational and first financial treatment and the years of education for the first financial treatment.

We expect our findings from our large academic campus in a metropolitan area to reasonably translate to other institutions at the forefront of the EV transition. First, the socio-demographic characteristics of our sample are consistent with the typical characteristics of early EV adopters in California (Lee et al., 2019): Using data from the California Air Resources Board's rebate applications, the average income, age, proportion of females, and homeowners are $206 thousand, 44 years, 27%, and 84%, respectively. In comparison, the corresponding values in our sample are $136 thousand, 38 years, 47%, and 54%. Second, early EV adopters from non-academic institutions are likely to face a similar combination of employees, many of whom may have more flexible work schedules and commuting patterns. It is worth noting, however, that our study population consists of UCSD affiliates who choose to charge at work and self-select into the study. Therefore, it is plausible that they are more responsive than the general population to our interventions. However, we would expect this subset to behave similarly to early adopters of EVs at such workplaces.

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* Table 2 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). The coefficients indicate how interventions influence each of the six measures of total workplace charging in a given week. First, the informational treatment did not significantly affect any measure of total charging, which suggests that the environmental appeal of daytime charging does not impact habits about where to charge (e.g., workplace vs. home).[21] This is consistent with results

[21] 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

from a similar, smaller trial experiment we ran in June 2023 (Table C4). Appendix A.6 describes the design of this trial experiment.

Second, the first financial discount, which reduced workplace charging prices by 50% (with discounted prices of $P^{work}_{small} = \$.14$ and $P^{work}_{large} = \$.07$ for the small and large discount group), led to an increase of 3.4 kWh in total weekly energy consumption and extended the weekly charge time by 39 minutes.[22] Relative to the weekly average of energy dispensed at the workplace, $E^{work}_{small} = 14.81$ kWh, this corresponds to a 23% increase in weekly energy consumption. We then estimate the price elasticity of workplace charging as the estimated percentage change in total energy dispensed at work between the small and large discount group, divided by the percentage change in the price for workplace charging, as given by:

$$\sigma = \frac{\frac{\Delta E^{work}}{E^{work}}}{\frac{\Delta P^{work}}{P^{work}}} = \frac{\frac{E^{work}_{large} - E^{work}_{small}}{E^{work}_{small}}}{\frac{P^{work}_{large} - P^{work}_{small}}{P^{work}_{small}}} = \frac{23\%}{-50\%} \approx -.46 \tag{3}$$

The estimated price elasticity of workplace charging therefore equals $-.46$. This indicates that EV drivers' workplace charging demand is orders of magnitude lower than the estimated price elasticity of off-peak home charging (-1.59) reported by Bailey et al. (2025), and the elasticities of -1.45 and -1 observed by Bernard et al. (2025) at public charging stations, yet marginally exceeds the estimated price elasticities for household-level consumption under time-of-use pricing (-0.1 to -0.2) in Harding and Sexton (2017). Since drivers did not alter their total energy consumption (i.e., the combined charging at work and away-from-work) in response to the large financial discount (Table C5), we infer that the elasticity of substitution between workplace and non-workplace charging – the percentage change in the ratio of energy charged at work relative to away-from-work for each one percent change in the relative price of workplace charging – is of similar magnitude to the price elasticity of workplace charging. These results highlight the lower flexibility of shifting EV charging to the workplace relative to shifting charging times at home.

In addition, the discount induced a higher average energy consumption and a longer session and charging duration per session, which suggests that the larger discounts are associated with longer sessions (Table C6).[23] This is consistent with the slight increase in energy

after the experiment (Table C3).

[22] The increase in total charging activity is reflected in the number of initiated charging sessions and total energy consumed between days 19 and 25 among individuals who receive the first large discount (Figure C1).

[23] Although the informational and second financial treatment do not exhibit significant effects on the average energy and 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 second financial discount. One plausible explanation is that discounts induce drivers to plug in earlier in the morning, leading to longer stays at work and longer duration sessions. In contrast, the informational treatment causes drivers to arrive later in the morning, resulting in shorter sessions.

Table 2: Effect on total charging behavior

	Total charging behavior					
	(1) Share	(2) Sessions	(3) Energy	(4) Session time	(5) Charge time	(6) Idle time
A. Information	1.714	-.009	-.541	-11.901	-5.611	-6.288
	(3.019)	(.077)	(1.499)	(27.798)	(20.071)	(13.503)
Weekly mean dep. var.	28.44	.77	13.17	242.54	169.34	73.19
B. Discount 1	.478	.037	3.403**	32.962	39.097*	-6.130
	(3.441)	(.086)	(1.668)	(30.152)	(20.670)	(15.666)
Weekly mean dep. var.	32.93	.86	15.3	273.64	194.16	79.47
C. Discount 2	-1.910	.126	1.746	34.051	23.902	10.162
	(4.173)	(.118)	(2.474)	(40.993)	(29.810)	(17.504)
Weekly mean dep. var.	28.95	.87	16.19	285.02	199.93	85.09
D. Information x large discount	-2.072	.008	.150	-13.521	-3.455	-10.064
	(2.908)	(.079)	(1.433)	(27.736)	(19.329)	(13.881)
Number of drivers	351	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 workplace charging (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session duration, in minutes (column 4); charging duration, in minutes (column 5); and idle duration, in minutes (column 6). The informational treatment, first financial treatment, and interaction effect are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual$\times$week. The weekly 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.

consumed on UCSD's "Clean Air Day" (Wednesday, October 4), a promotional event with a 50% discount on the workplace charging rate (Appendix A.7). These results suggest that the large discount encouraged additional drivers to charge at work and motivated drivers who already use workplace charging to charge their vehicles with more energy per session. These findings suggest that the treatment is more likely to influence the behavior of existing drivers by extending their charge, rather than inducing entirely new charging routines among those who do not typically rely on workplace charging.

Third, in contrast to the first financial discount, the second financial discount (in which half of the large discount group continued with the large discount) did not lead to a statistically significant change in total workplace charging. The point estimate on energy charged per session is approximately half the size of the estimate from the first phase (1.7 kWh). This is also reflected in the weekly mean share of charging done at work, which decreased from 33% to 29% between the first and second financial treatments. We attribute the smaller effect on total charging during the second financial discount to shifts in the timing of initiated charging sessions: providing large discounts to fewer drivers reduced the perceived scarcity of available chargers and led fewer drivers to arrive early in the morning to secure the associated discounts. While we interpret this as evidence against strong habit formation, the attenuation in estimated effects between discount phases could be consistent with partial habit persistence: drivers may have internalized some of the behavioral adjustments during the first phase, such as late evening charging, but responded less strongly once the perceived scarcity of chargers diminished in the second discount phase.

2. *Effect on the timing of charging behavior* Next, we transition to temporal shifts in charging behavior. Figure 2 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). To calculate total energy delivered, we assume that energy is dispensed uniformly to the EV while actively charging.[24] 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.

Receiving environmental nudges led to a decrease in charging sessions initiated between 5–7 am and a slight increase in initiated sessions between 7–10 am (Panel A). In addition,

[24] ChargePoint chargers dispense energy continuously from the time a charging session begins until the vehicle is fully charged or unplugged. However, ChargePoint chargers have two ports, so the nominal 6.6 kW throughput may fall (or increase) by 3.3 kW if another EV starts (or stops) charging during the session. PowerFlex chargers ask drivers to specify their desired charging duration and mileage to add as inputs to an automated load management algorithm that modulates the start time or kW throughput if there is surplus time to meet the requested mileage, potentially concentrating energy dispensed throughout the session.

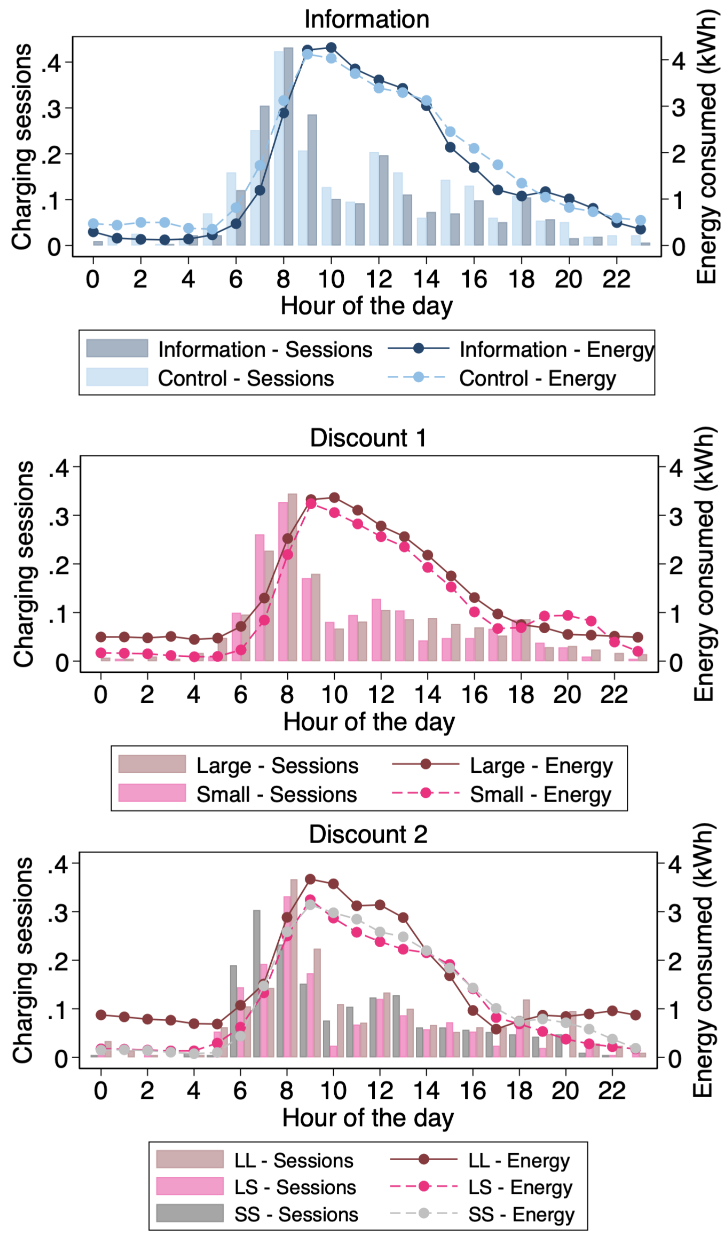

Figure 2: Number of charging sessions and energy consumed by hour of the day

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. The energy consumed equals the uniform dispensation of power to the electric vehicle during active charging.

we observe a reduction in initiated sessions between 3–9 pm. Conversely, the first financial intervention shifts charging to 5 am and 9-11 pm for the large-discount group (Panel B). During the second financial intervention, we observe that the LL discount group shifts to even earlier evening and overnight sessions between 6-10 pm (Panel C). While both groups that received the first financial discount (LL and LS) show a shift to initiating sessions at 5 am, we observe an increase in charging between 6-7 am for the SS group.

Consequently, environmental prompts seem to contribute to postponed scheduling of morning sessions and fewer late afternoon and evening sessions–both of which better align charging with solar energy generation. Larger financial incentives induced a shift to earlier morning and overnight charging, driven by greater evening arrivals at work.

Table 3 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 coefficients indicate how our interventions influence the number of initiated charging sessions per driver during the five distinct periods in a given week.[25] The informational treatment resulted in a significant decrease of .041 weekly early morning charging sessions (5–7), which was compensated by an increase of .085 sessions during the morning (7–10). Given an average of .77 weekly workplace charging sessions per driver, around 5.3% of weekly sessions were shifted away from early morning. This indicates an intertemporal substitution effect, wherein the environmental prompts induced a shift from early morning toward daytime charging when solar energy generation is more abundant.[26]

Conversely, the first financial discount for workplace charging yielded a significant increase of .042 early morning (5-7) and .029 overnight sessions (21-5). This corresponds to a shift of 4.9% and 3.3% of the weekly workplace charging sessions per driver due to the first discount. This pattern suggests an intertemporal substitution in the opposite direction – outside of the solar midday period. This is consistent with charging behavior during the Clean Air Day, which saw drivers initiate earlier charging sessions (Figure A6, Panel B).

Finally, we observe a significant decline of .112 charging sessions (12.9%) in the evening period (16–21) among drivers who were assigned to smaller discounts in the second phase (LS), compared to those who continued receiving large discounts (LL). As the timing of

[25] In addition to the intra-day shifts of charging sessions, commuters may also respond to our interventions by shifting to weekend charging sessions or reducing energy from (non-discounted) DC Fast Chargers. However, we do not find any evidence of intra-week substitution of charging sessions or substitution from DC Fast Chargers (Table C5).

[26] Consistent with the idea that environmental motivation is a determinant of EV charging timing, we find that primarily individuals who report high environmental motivations for charging reduce their early morning sessions during the informational treatment, while individuals who report low environmental motivations increased their late evening and overnight charging as a response to financial discounts (Table C7).

initiated charging sessions of drivers who received reduced discounts reverted to those receiving the small-small sequence of discounts (Table C8), drivers' charging behavior reflects an absence of habit formation after the first financial treatment. The shift from overnight to earlier evening charging may indicate that commuters adapted their routines to charge during periods when a greater number of chargers are reliably available for overnight charging. As our study occurred over a relatively short timeframe, the estimated treatment effects should be interpreted as short-term effects and drivers may require a longer horizon to form charging habits. The smaller shift to early morning charging 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 to the small discount). One additional explanation is that the financial incentives led to an immediate but temporary shift to morning sessions, consistent with the fact that the discount caused a shift to early morning charging (Table C3) and total energy consumed (Table C9) solely in the first week of the first financial intervention.

To examine which drivers respond to the interventions, Table C10 reports the effects on charging timing by affiliation. The environmental nudge primarily prompted staff to shift charging from early to later morning, while commuting students reduced early-morning charging and students living on campus increased charging during the later morning period. During the first financial discount, the shift toward early-morning and overnight charging was again largely driven by staff, with faculty exhibiting a smaller, non-significant increase in early-morning sessions. In contrast, the increase in late evening charging during the second discount period was mainly attributable to commuting students, particularly those charging on West and East Campus (Table C11), suggesting that these students likely leave their EVs on campus overnight.

Table 3: Effect on the timing of charging

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Information	-.041*	.085*	-.028	-.021	-.006
	(.024)	(.050)	(.039)	(.028)	(.010)
Weekly plug-ins per driver	.06	.32	.24	.12	.03
B. Discount 1	.042**	.007	-.015	-.027	.029**
	(.020)	(.055)	(.044)	(.036)	(.014)
Weekly plug-ins per driver	.07	.38	.25	.13	.04
C. Discount 2	-.035	-.026	.056	.112**	.028
	(.035)	(.063)	(.061)	(.053)	(.030)
Weekly plug-ins per driver	.09	.36	.31	.14	.05
D. Information x large discount	-.026	.062	-.005	-.023	-.001
	(.020)	(.053)	(.038)	(.033)	(.010)
Number of drivers	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 early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment, first financial treatment, and interaction effect are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, as well as garage-fixed effects. All coefficients are reported in individual×week. The weekly number of initiated charging sessions per driver is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

These results highlight important considerations for generalizability. University staff (as opposed to students or faculty), whose demographics may more closely resemble those of the general population, appear to be the most responsive to both informational and financial interventions. In congested charging networks, the shift among staff toward early morning sessions is a behavior likely to emerge in other workplaces with limited charger availability, while the shift toward later morning charging could similarly translate to workplaces seeking to nudge employees toward aligning charging with solar generation. Hence, the role of charger and parking availability in mitigating increased competition for early morning charging induced by price discounts is likely transferable to other workplace contexts and carries clear policy implications for investment in workplace charging infrastructure. In contrast, the shifts to late evening and overnight charging, particularly among commuting students, appear to reflect home charging by those living near campus or ridesharing with other students, rather than patterns typical of most workplaces, and thus may have limited relevance beyond the university context.

C. Mechanisms

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

We focus on these mechanisms for three reasons. First, scarcity concerns emerged as a potential explanation for the temporal shifts in the first financial experiment, with greater early morning charging indicating intensified competition for chargers due to limited availability. Second, drivers have reported difficulty finding an available and reliable charger at work in the enrollment survey, aligning with existing literature highlighting these as common shortcomings in public charging infrastructure.[27] report that only 73% of DC Fast Charger ports sampled in the Bay Area in 2022 were operational, far below the 95–98% range claimed by EV charging service providers. Third, analyzing driver characteristics is critical for identifying which demographic groups respond to our interventions, thus informing future interventions targeting the most responsive groups. Understanding the mechanisms can help institutions and policymakers predict temporal shifts in charging behavior depending on the characteristics of their charging networks, incentives, and commuters.

1. *Experimental incentive structure.* Financial discounts themselves could increase drivers' perceptions of scarcity if drivers believe lower charging rates induce greater workplace-wide charging. Figure B7 suggests an almost 10% surge in hourly PowerFlex charger utilization from the informational to the first financial discount at 9 am on the first Monday of the intervention period, giving drivers reason to associate network scarcity with discounts. An "induced" expectation of additional network use could decrease drivers' willingness to charge at work or deviate from existing charging patterns in response to discounts.

To test whether perceived incentive-induced scarcity contributed to temporal shifts in workplace charging during the interventions, we conduct a follow-up financial intervention similar to the first financial intervention, but that additionally primes drivers' beliefs about how many EV drivers receive the discount (Appendix A.8). In this follow-up intervention, the

[27] Charger unreliability is a known impediment to EV adoption and charging. For example, Rempel et al. (2024)

scarcity treatment group received a notification implying that the entire Triton Chargers EV club would get the discount, while the control group received a similar notification implying that only one-third of the club would receive the discount.

Table 4: Effect on the timing of charging by scarcity

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Induced scarcity	-.046*	-.025	.050	.056**	.020
	(.026)	(.046)	(.037)	(.028)	(.018)
B. Discount	.051	-.000	.022	.002	.026*
	(.032)	(.048)	(.038)	(.029)	(.015)
C. Scarcity x large discount	-.003	-.033	.044	.035	.040
	(.027)	(.053)	(.048)	(.033)	(.027)
Weekly plug-ins per driver	.08	.34	.21	.12	.04

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

Expectations of incentive-induced scarcity resulted in a shift from early morning to late evening charging sessions equivalent to the transition from the first to the second financial discount intervention (Table 4). This suggests that drivers' scarcity concerns of increased competition for chargers in the morning, as in the first financial experiment, prompted them to seek charging during low-utilization periods in the evening. Drivers' expectations of additional incentive-induced workplace charging had an impact equivalent to the incentives themselves. Notably, the temporal shifts to early morning and overnight charging sessions of the large financial discount during the scarcity experiment closely mirror those of the first financial discount intervention.[28] Thus, the incentive-induced perception of scarcity can

[28]The effect of the charging discount on energy consumed and session duration during the follow-up experiment align with the effects on total charging behavior during the main experiment (Table C12).

explain some of our observed shifts during the financial intervention toward evening charging when the network is less congested.

2. *Quality of charging infrastructure.* In addition to the experiment-induced scarcity concerns, we test two charging network attributes that plausibly affect drivers' charging decisions. The first is high network utilization, defined as the fraction of chargers used during a given hour, which could discourage drivers from charging at work. As Figure 3 illustrates, by 9 am the two largest campus zones (West Campus and East Campus) typically experience 80–90% weekday utilization, while all other zones experience over 50% utilization.[29] Periods of high utilization largely align with periods of low grid carbon intensity.

To empirically estimate whether network utilization is a mediating factor in our estimated temporal shifts in workplace charging during the interventions, we run separate regressions for drivers who typically charge at low, medium, and high utilization garages – defined as garages with $\leq 60\%$, $60-75\%$, and $\geq 75\%$ utilization, respectively, during the morning commute period (7 – 12 pm). We observe that the informational and financial interventions affect drivers who typically charge in low- and high-utilization garages differently (Table C13). In response to informational prompts, the drivers who shift to later morning charging are exclusively those who typically charge in low-utilization garages, which suggests that drivers' responsiveness is higher when there is no charger scarcity. In contrast, the shift toward overnight and late evening periods during the financial discounts predominantly reflects drivers who use medium- and high-utilization garages shifting to periods with lower utilization to guarantee they receive a charge.[30] Consistent with drivers' concerns about charger scarcity, these temporal shifts induced by the financial discount occurred primarily in campus zones with high network utilization (Table C11).

The second network attribute that could discourage drivers from charging at work is the perceived unreliability of chargers. We measure this unreliability of chargers as the percentage of charging sessions that "glitch" (i.e., that fail to deliver a meaningful energy), which varies between 15 to 20% daily for PowerFlex and ChargePoint chargers at work (Figure B9). Of all attempts to charge during our study, only 86% yielded meaningful energy (> 0.5 kWh).[31] Moreover, drivers who unsuccessfully plug in on their initial attempt

[29]We calculate "effective" network utilization, which excludes chargers that are temporarily non-operational or out-of-service (Appendix B.3). These estimates represent a lower bound because we do not detect when stalls are occupied by non-charging vehicles (e.g., non-EVs parked in an EV station or EVs exploiting parking spots without charging). Appendix B.4 summarizes network utilization at UCSD.

[30]The shift to earlier morning charging sessions during the first discount occurs mainly in low-utilization garages. These shifts may reflect an expectation that large discounts on charging will intensify competition for highly utilized chargers during peak periods and, therefore, only cause a shift among drivers who face lower utilization early in the morning.

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

are less likely to receive a charge during immediately consecutive attempts (Figure B10).

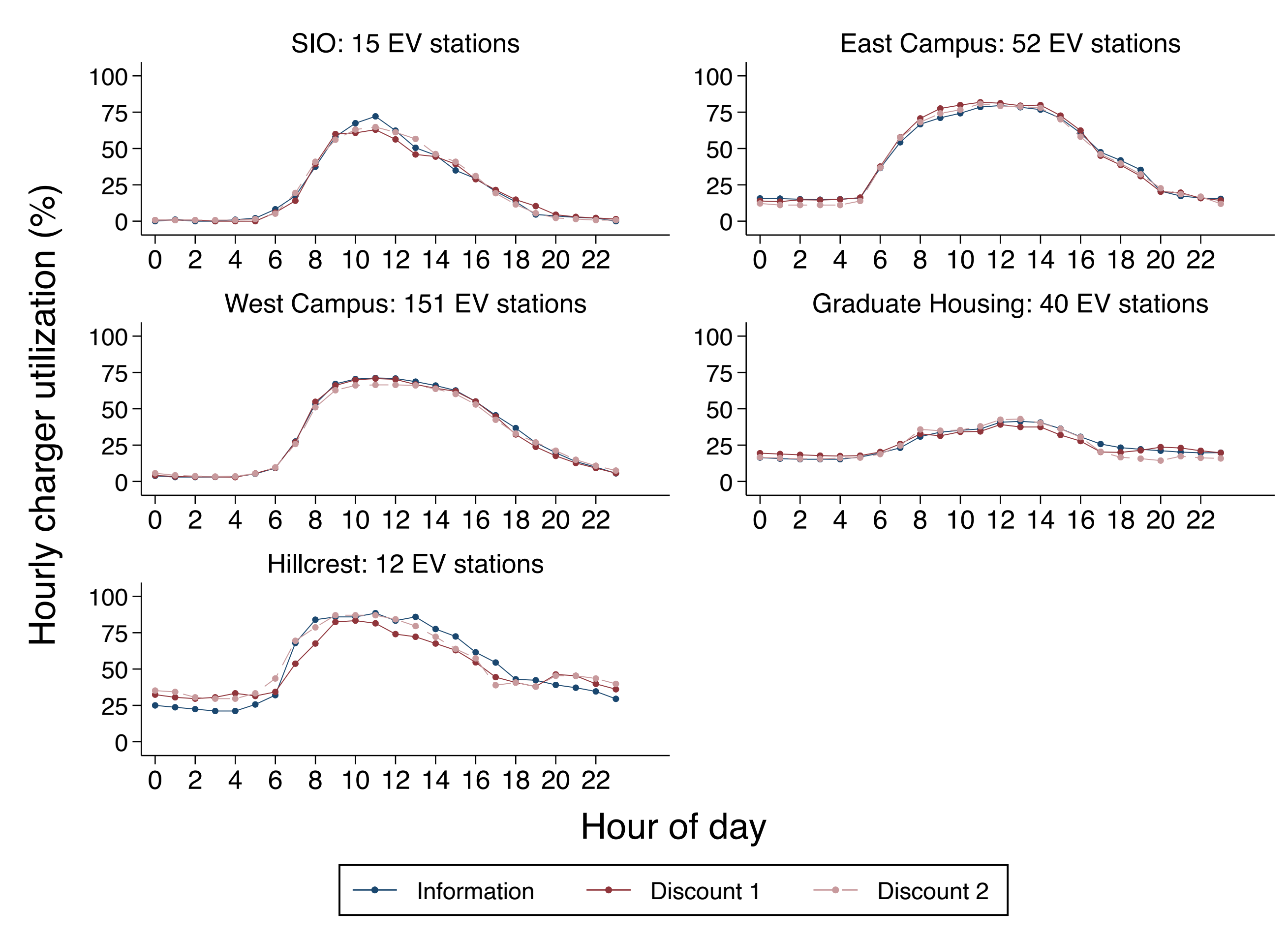

Figure 3: Network utilization by time of day and campus zone

Notes: This figure shows the effective hourly utilization of chargers for the five campus zones over the experiment period (October 5 - November 19). Results are the average, by hour, of all weekdays in the experiment period. We define the effective hourly charger utilization as the percentage of chargers used in a given hour relative to all chargers used during the experiment period. We exclude chargers that are non-operational and out-of-service. Figure B1 shows the five distinct parking zones on the UCSD campus.

Because these failed attempts occur more frequently in particular garages, we assess whether charger unreliability was a cause of the temporal shifts in workplace charging by comparing drivers who experience a low ($\leq 10\%$), medium ($10 - 20\%$), and a high rate of failed sessions ($\geq 20\%$), or "glitch rate," at their modal garage. Consistent with the hypothesis that drivers are more willing to shift their charging behavior when chargers are

app connectivity. One possible explanation for the low reliability of charging networks is that operating a charging station has not been profitable for many charging companies, meaning few resources are available for maintenance (Campbell, 2024).

reliable, drivers who charge at low- and medium-glitch-rate garages lead most temporal shifts in charging during the financial interventions (Table C14).[32]

3. *Driver characteristics.* Drivers with greater flexibility in their decisions about when to commute to work and charge may be better able to adapt their commuting and charging schedules in response to nudges and discounts (Kacperski et al., 2022). To test whether greater commuting flexibility influences charging behavior, we compare the temporal shifts of drivers with different commute frequencies. Given our context as a workplace charging network, we identify drivers who commute frequently ($\geq$ 3 times per week) as possessing higher flexibility, as they can select from several days for charging. Frequent commuters are solely responsible for the shift to evening and overnight sessions during the first and second discount (Table C15), suggesting that commuter groups with greater flexibility are more likely to adjust their charging schedule. Overall, we observe a slight substitution in total charging behavior from infrequent to frequent commuters (Table C16), indicating a redistribution of total workplace charging between these commuter groups.

An additional driver characteristic that could limit the use of workplace charging is access to private home charging and low-cost overnight charging rates, potentially deterring the use of workplace charging (Jabeen et al., 2013). Consistent with this mechanism, we find that providing financial discounts induces large shifts to evening and overnight charging sessions from drivers without a home charger (Table C17) or those who report paying high modal prices for charging at their usual location (Table C18). These results imply that the convenience of residential charging for treated drivers plays a key role in how financial incentives shift the timing of charging sessions.[33] In addition, our interventions also prompted an increase in total energy consumed for drivers who report paying high modal prices for charging at their usual location (Table C20), which suggests that financial interventions have a more pronounced effect on these commuters.

IV. Policy implications

A. Environmental effects from EV charging

In this Section, we calculate the *fiscal abatement costs* (expressed in \$ per ton of CO_2) of our interventions. We derive the abatement costs as the ratio of the differential costs between the

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

[33]These interventions solely shift the timing of charging among battery EV drivers, who have larger batteries, require longer charging durations, and lack alternative fuel options, unlike plug-in hybrid drivers who may view the discounts as beneficial but ultimately non-essential (Table C19).

large- and small-discount groups (i.e., consumed energy multiplied by the respective discount rates) relative to the change in total CO_2 emissions resulting from shifts in the timing of workplace charging and the relocation of charging activity from home to the workplace:

$$\text{Fiscal abatement costs (\$ per ton CO}_2) = \frac{E_\ell \cdot \$0.23/\text{kWh} - E_s \cdot \$0.16/\text{kWh}}{\Delta \text{CO}_2}. \tag{4}$$

E_l and E_s refer to the total annual energy consumed by the large and small discount groups. Converted to an annual basis, the incentives paid to the average participant were \$209.6 for the large and \$123.6 for the small discount in the first financial treatment, implying a financial cost of \$86 annually.

To estimate the change in CO_2 emissions, we calculate how our interventions affect commuters' charging-related CO_2 emissions.[34] The first part equals the hourly charging-related CO_2 emission changes at work that arise through the information and financial treatments for each hour h. The second part aggregates the changes in hourly energy consumption per day and adjusts by the total effect on energy consumed to reflect that the total energy dispensed for EV charging remains constant. We thereby assume that any energy from charging brought to work leads to an equivalent reduction in energy dispensed from typical away-from-work charging.[35] Equation (5) displays the change in charging-related CO_2 emission per driver annually from our interventions:

$$\begin{aligned} \triangle CO_2 = & \sum_{h=1}^{24} \underbrace{(\beta_h^{kWh} \cdot CI_h + \delta_{1h}^{kWh} \cdot CI_h + \delta_{2h}^{kWh} \cdot CI_h)}_{\textit{Timing work charging}} \cdot \; SCC \\ & - \underbrace{(\beta^{kWh} \cdot \overline{CI} + \delta_1^{kWh} \cdot \overline{CI} + \delta_2^{kWh} \cdot \overline{CI})}_{\textit{Shifts home charging}} \cdot \; SCC, \end{aligned} \tag{5}$$

where β_h^{kWh}, δ_{1h}^{kWh}, and δ_{2h}^{kWh} indicate the effect of informational, first financial, and second financial treatment on total energy consumption during hour h. The coefficients refer to the effect on average hourly energy consumption between the plug-in time and the end of the charge. CI_h refers to the marginal hourly carbon intensity (gCO_2/MJ) per the LCFS program.[36] β^{kWh}, δ_1^{kWh}, and δ_2^{kWh} indicate how the informational, first financial, and second

[34] We exclude potential changes in office electricity usage from adjustments in commuting schedules, as their per capita energy consumption is negligible compared to EV charging.

[35] As our interventions did not significantly affect the total vehicle miles traveled or energy dispensed at work for drivers who responded to recurring odometer readings (Table C5), we assume that drivers did not change their total energy consumption. This aligns with existing work on the rebound effect in the context of fuel efficiency, which suggests that the rebound effect in personal vehicle travel tends to be small (Gillingham et al., 2013).

[36] We assume that the carbon intensity of electricity is the same for home and workplace charging; the environmental benefits come purely from changes in the timing of charging rather than differences in location-specific grid emissions. To transform the carbon intensity factor from gCO_2/MJ into tCO_2/kWh, we

financial treatment affect the total energy consumption per day (column 3, Table 2). $\overline{CI}$ denotes daily CO_2 emissions from the average charging profile of Triton Charger EV club members.[37] Multiplying this by the Environmental Protection Agency's (2022) social cost of carbon (SCC) of 210 $\frac{\$}{tCO_2}$ yields the total cost of CO_2 emissions.

Table 5 reports the environmental impact of avoided CO_2 emissions resulting from the temporal and total shifts of charging for each intervention (equation 5). We express the change in charging-related CO_2 emissions per driver as a percentage of the total social costs associated with CO_2 emission damages from EV charging. Appendix D.1 outlines how we combine the charging network and driver data to estimate the social costs of CO_2 emission damages from EV charging. The social workplace and home charging CO_2 emission damages from charging are equal to \$140.2 (.67t CO_2) per driver annually.

Table 5: Environmental effects from EV charging

	Effect per driver (%)		
	Information	Discount 1	Discount 2
Avoided CO_2 emissions ($\triangle CO_2$)			
Due to timing of work charging	3.07	−7.21	−5.84
Due to shift in home charging	−1.90	8.69	3.90
Total environmental impact ($\triangle E^{societal}$)	1.17	1.48	−1.94

Notes: This table reports the environmental effect measured as the percentage change in carbon emissions per equation (5) due to the temporal and total shifts of charging for each intervention – the informational (column 1), first financial (column 2), and second financial treatment (column 3). The environmental effect represents the average change in carbon emissions. The effects associated with each discount period represent the impact of the large discount relative to the small discount levels.

The temporal shifts in workplace charging induced by the informational treatment reduced CO_2 emissions by 3.07%, as drivers shifted charging to later morning periods when grid carbon intensity is relatively low. As grid carbon intensity generally increases in the evening due to declining solar generation and higher demand triggering fossil-fuel generation, the first and second financial discounts led to increases in emissions of 7.21% and 5.84%, respectively, reflecting more frequent early morning and overnight charging during periods of elevated grid carbon intensity.

In terms of aggregate shifts in charging behavior, the informational intervention reduced the energy consumed at work, while the financial incentives led to additional energy dispensed

multiply CI_h by 3.6 $MJ/kWh \cdot 10^{-6} t/g$.

[37] We derive the average daily carbon emissions from charging by multiplying the hourly carbon intensity with the self-reported percentage of charging during four different times of the day: Morning (6am-12pm), afternoon (12-4pm), evening (4-9pm), and night (9pm-5am).

from workplace charging. As workplace charging has a lower carbon intensity than the typical charging profile reported by Triton Charger Club members, the environmental effect of shifting charging to work is positive. Hence, the total shift away from workplace charging during the informational intervention increased CO_2 emissions by 1.9%.[38] In contrast, the increase in total energy consumed at work during the financial discount periods led to a CO_2 reduction of 8.09% and 3.9%, respectively. Although financial incentives led to workplace charging during higher carbon intensity periods, the shift from home to workplace charging mitigates a significant portion of this increase and surpasses the environmental damages from the temporal shifts during the first discount. Therefore, the environmental implications of discounted workplace charging are initially positive due to the temporary effect on early morning sessions but gradually become damaging as charging shifts to overnight periods.

Overall, the informational treatment led to a 1.17% increase in avoided CO_2 emissions, which resulted from a shift to workplace charging with lower grid intensity. The net effect of the first financial treatment resulted in a CO_2 reduction of 1.48%, primarily due to shifting from home to work charging. However, as drivers shifted gradually to late evening charging hours with higher grid intensity, the net effect of the second financial treatment resulted in a CO_2 increase of 1.94%. If scaled to all EV owners in California, the informational treatment and first financial treatment would avoid \$2.12 million and \$2.67 million in CO_2 emission damages per year, whereas the second financial discount would inflict \$3.5 million in CO_2 emission damages.

Finally, by incorporating our cost and CO_2 emission estimates into the abatement cost equation (4), we find that the first financial discount, with an annual cost of \$86 per driver, reduced emissions from EV charging by 9.9 kilograms of CO_2. This translates into an implied abatement cost of approximately \$8,725 per ton of avoided CO_2 emissions, suggesting that financial demand-side interventions are costly for reducing EV charging emissions. In contrast, environmental nudges can be cost-efficient if annual informational campaign costs for daytime charging remain below \$1.64 per driver assuming a SCC of \$210 per ton.

From a policymaker's perspective, the fiscal abatement cost estimates from the workplace discounts are interpreted in terms of financial expenditures; therefore, our baseline calculation focuses on fiscal outlays rather than resource costs.[39] However, in California, retail electricity rates are often more than twice the social marginal cost (SMC) due to recovery for fixed infrastructure, wildfire mitigation, and policy mandates (Borenstein & Bushnell,

[38] As we assume no changes in the timing of away-from-work charging, this estimate of our informational prompts may serve as a higher bound for the environmental effect.

[39] Resource costs refer to the economic inputs required to produce and deliver electricity, including fuel, variable operations and maintenance, and transmission and distribution costs. The SMC consists of the resource costs plus any environmental externalities.

2022). This suggests that, under both the small and large discount, the effective workplace charging prices remained largely above the SMC of electricity. From an economic perspective, these financial costs largely reflect a transfer of surplus from the utilities (or taxpayers) to EV drivers rather than a resource cost. Consequently, the resource costs of the abated CO_2 from our workplace charging discounts are likely to be substantially lower and depend on how the discounts affect the LMP of electricity through shifts in charging patterns.

B. LCFS revenues

The institution that hosts the charging network can generate revenues from shifts in workplace charging usage and timing through California's LCFS program. The LCFS is designed to increase the availability of low-carbon alternative fuels, while reducing petroleum dependency, the carbon intensity of California's transportation fuel pool, and air pollution. From the institution's perspective, LCFS revenues accrue when charging is brought to work, while shifts toward home charging accrue to the state's electric utilities.[40] Hence, we abstract from changes in LCFS revenues from home charging as the utilities' LCFS credits are a pass-through that goes to electrifying the transport sector.

Specifically, we estimate the change in LCFS revenues resulting from temporal shifts in workplace charging by multiplying the hourly change in electricity consumption by the corresponding carbon intensity of electricity (Appendix D.2). Based on the LCFS revenue calculation in equation (D3), we estimate that the financial incentives increased LCFS revenues for the institution hosting the workplace charging by 22.39% and 7.6%, primarily reflecting the shift of charging activity from home to the workplace. This implies that the discounts on workplace charging led to a redistribution of LCFS revenues from the local utility company to the institution that hosts the charging network. Additionally, the informational prompts decreased the institutions' LCFS revenues by 3.49% as drivers shifted away from workplace charging. From the perspective of UCSD, summed over all Triton Charger club members, the two financial interventions increased annual LCFS revenues by $6,420, and $2,179, respectively.

C. Distributional effects

A common objection to providing financial incentives for charging is that the benefits accrue unevenly across socioeconomic groups. Figure 4 presents the distributional profile of the

[40] Under the LCFS, credits are generated whenever an EV driver charges their vehicle at home. The state's electric utilities receive credits for at-home charging in their respective service territories. However, the utility companies must put the proceeds from LCFS credit sales toward programs to support their residential customers who own or lease an EV.

financial discounts across six income brackets in our study population. Normalized by group size, the uptake of discounts is roughly uniform across income brackets. However, because EV drivers skew wealthier in our study and in observed adoption trends, high-income households earned most of the financial discounts for workplace charging. While we paid $\$1,706$ in discounts to the highest income group, the lowest income group received only \$221. Given that current EV drivers are wealthier, providing discounts to shift these individuals' 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.

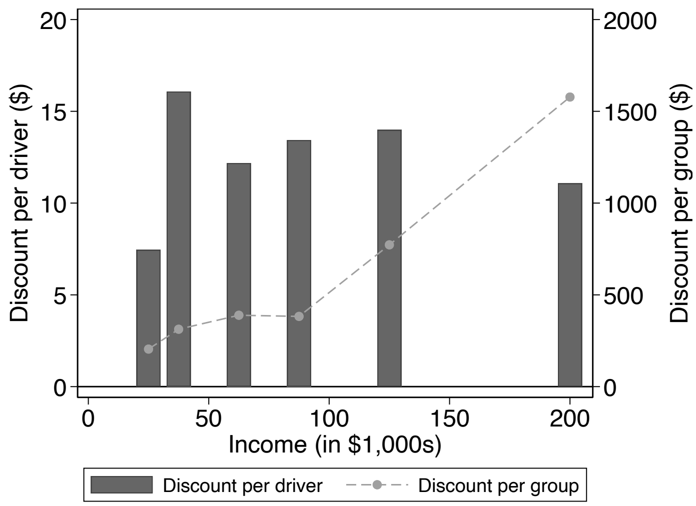

Figure 4: Discounts by income

Notes: This figure shows the discount 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). The six groups report household incomes (in \$1,000s) of $\leq$ \$25; \$25-\$50; \$50-\$75; \$75-\$100; \$100-\$150; and $>$ \$150.

V. Conclusion

As the market for EVs 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 supplying their increased energy demand from renewable sources. As electric grids transition toward renewable resources, particularly solar, they have large variations in marginal emissions throughout the day. For a solar-abundant grid, such as in California, clean and efficient EV charging will require temporal shifts toward midday when most people are at work (Gillingham et al., 2021). As EVs proliferate and renewable energy capacity increases, policies should encourage a shift to daytime charging to optimize power usage.

The empirical findings of our field experiment at UCSD can inform workplace policy aimed at encouraging sustainable daytime charging. Our interventions induced opposing shifts in 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, location-specific financial discounts spurred drivers to charge earlier in the morning and later in the evening, outside the optimal period. In addition, the charging discounts encouraged drivers to charge at work and with more energy per session. The results highlight the importance of environmental knowledge about daytime charging to reshape daily charging patterns and the adverse effects of time-invariant price mechanisms to achieve workplace charging in congested networks.

Understanding the underlying mechanisms is vital for developing effective policies and identifying drivers most amenable to these policies. We document three clusters of mechanisms that explain the observed temporal shifts. First, commuters' perceptions of charger availability resulted in overnight charging sessions. Second, driver's responsiveness to off-peak charging hours hinges on the utilization and reliability of the network. Third, high-frequency commuters and drivers without access to low-cost charging away-from-work were among the most responsive groups. We highlight that the charging-induced shifts from our interventions can contribute to a substantial CO_2 emission reduction of EVs and generate LCFS revenues for the workplace that hosts the charging network. The experiments at UCSD mark the start of an evidentiary basis for understanding and shaping driver charging behavior at workplaces. However, understanding how more nuanced discount structures (e.g., time-based or kWh-based) might encourage preferred charging behavior or how to encourage deeper charge sessions to achieve higher network utilization requires more research.

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Appendix

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

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Sebastian Tebbe *David Victor*

A. Experimental design

This Section provides additional details about EV drivers at UCSD (Section A.1), informational prompts (Section A.2), emails notifying participants about financial discounts (Section A.3), the experimental schedule (Section A.4), the Triton Charger EV club members (Section A.5), our Spring trial informational experiment (Section A.6), Clean Air Day (Section A.7), and our follow-up charger scarcity experiment (Section A.8).

A.1. EV drivers at UCSD

EV chargers at UCSD are available for use by UCSD affiliates (faculty, staff, students) and the general public. All charging session data are logged by the charger vendors and (once anonymized) may be used by the UCSD Transportation Services Office for operational (non-research) purposes. Any EV driver, whether a campus affiliate or just a member of the public, can access the base workplace charging rate set by the Transportation Office. During our experiments, the base rate was $\$.30/kWh$ for Level-2 charging on weekends and $\$.35/kWh$ on weekdays. To promote EVs and help plan transportation electrification at work, the Transportation Office offers a $\$.05/kWh$ discount on weekdays (15% off the base rates) to affiliates who sign up, provide demographic and housing information, and connect their 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 in return for additional information and discounts on workplace 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. Drivers also respond to recurring (usually twice monthly) surveys that request an odometer reading and updates about their EV. 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 workplace charging activity as the session level.

A.2. Informational prompt

The treatment in the informational experiment consists of an emailed prompt (text below) and the infographic (Figure A1):

- [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.

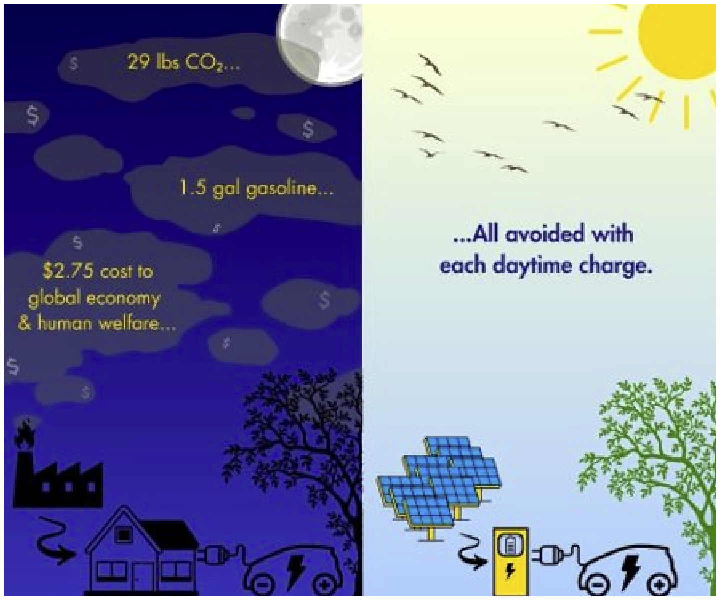


Figure A1: Infographic included with the informational prompt

A.3. 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.4), though these were not part of the analytical experiment.

A.4. Experimental schedule

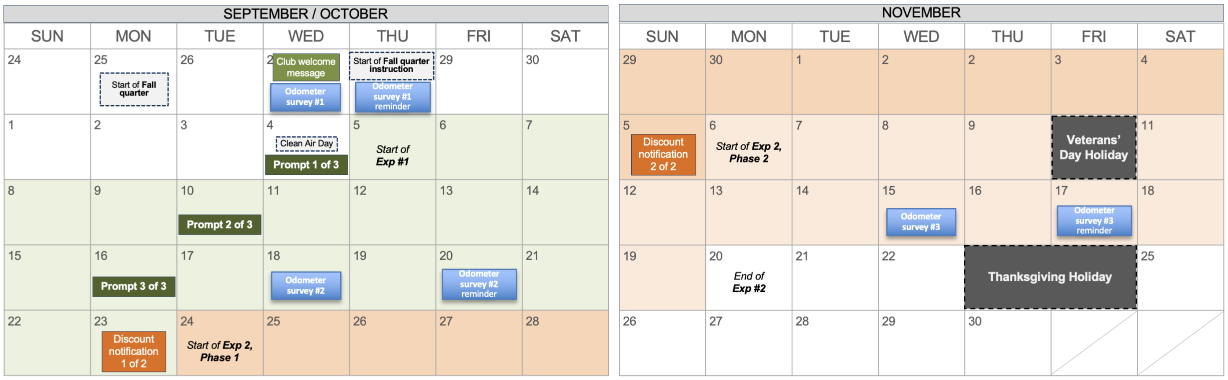
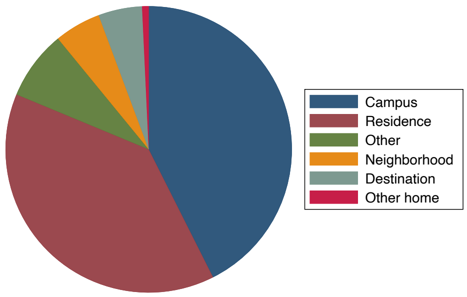


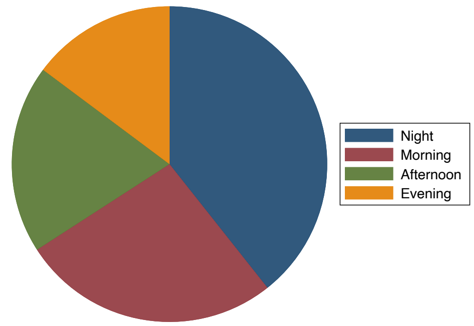
Figure A2: Experimental schedule for the three interventions

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 5 to October 23), first financial (October 24 to November 5), and second financial (November 6 to November 19) 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. Clean Air Day (a non-research campus promotional day) was October 4; the Transportation Office notified the campus community on October 3. 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.

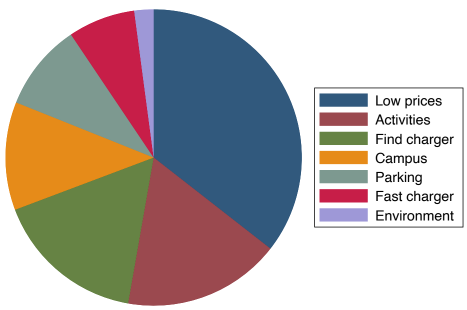
A.5. Triton Charger EV club members



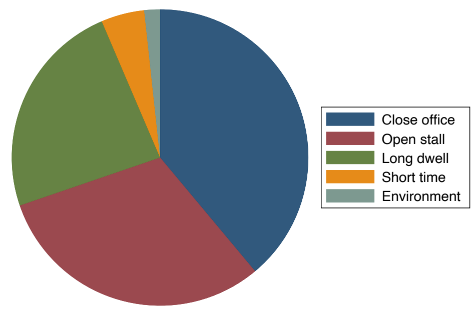
(a) Charging location



(b) Charging time



(c) Charging motivation



(d) At-work charging

Figure A3: Supplementary charging characteristics

Notes: This figure reports charging behavior patterns based on location (Panel A), time of day (Panel B), reasons for charging (Panel C), and motivation to charge at work (Panel D) for experiment participants from the Triton Chargers EV club enrollment survey prior to the experiment.

Table A1: Balance table

	Information		Discount 1		Discount 2	
	Treated	Control	Large	Small	Large-large	Large-small
A.Demographics						
Age	38.58	37.92	38.48	37.79	38.35	38.61
	(13.33)	(12.43)	(12.65)	(13.34)	(12.36)	(12.36)
	[.52]		[.53]		[.89]	
Share male (%)	0.50	0.57	0.58	0.45	0.55	0.61
	(.5)	(.5)	(.49)	(.5)	(.5)	(.5)
	[.06**]		[.0***]		[.59]	
Income ($1,000s)	138.39	133.03	136.69	133.82	137.09	136.28
	(66.21)	(66.97)	(66.94)	(66)	(66.45)	(66.45)
	[.34]		[.63]		[.73]	
Years of education	17.32	17.04	17.40	16.74	17.47	17.33
	(3.14)	(3.04)	(3.06)	(3.11)	(3.17)	(3.17)
	[.24]		[.01**]		[.1]	
Days at work per week	3.23	3.29	3.28	3.22	3.28	3.27
	(1.75)	(1.76)	(1.76)	(1.74)	(1.76)	(1.76)
	[.69]		[.72]		[.82]	
B.Vehicle attributes						
Vehicle age (years)	2.40	2.37	2.44	2.27	2.50	2.39
	(2.87)	(2.29)	(2.69)	(2.4)	(2.68)	(2.68)
	[.88]		[.41]		[.45]	
Battery electric (%)	0.76	0.77	0.75	0.80	0.79	0.70
	(.43)	(.42)	(.44)	(.4)	(.41)	(.41)
	[.66]		[.17]		[.25]	
Odometer reading (1,000 miles)	31.56	30.59	31.77	29.79	32.56	30.93
	(31.5)	(27.17)	(28.9)	(30.34)	(27.87)	(27.87)
	[.73]		[.5]		[.45]	
C.Commuting and charging habits						
Daily mileage (miles)	34.27	38.38	36.53	35.93	37.74	35.10
	(27.81)	(30.28)	(26.94)	(32.66)	(29.53)	(29.53)
	[.18]		[.85]		[.5]	
Home charger (%)	0.59	0.58	0.59	0.58	0.59	0.60
	(.49)	(.49)	(.49)	(.5)	(.49)	(.49)
	[.78]		[.72]		[.94]	
Charging price ($ per kWh)	0.18	0.18	0.18	0.19	0.17	0.19
	(.12)	(.12)	(.12)	(.12)	(.12)	(.12)
	[.55]		[.42]		[.12]	
Number of Observation	315	314	418	211	210	208

Notes: The table presents the average values and balance tests on driver demographics (Panel A), vehicle attributes (Panel B), commuting and charging habits (Panel C) for treated and control groups of the informational, first, and second financial intervention. Robust standard errors are in parentheses. We report the p-values from a two-way t-test for differences in means across the treatment group and the control group in backets. *, **, *** refer to statistically significant different p-values with 90%, 95%, and 99% confidence, respectively. Driver data are from the Triton Chargers EV club enrollment survey prior to the experiment. We report averages for age, income, and education, while our survey data asked respondents to select the appropriate bracket for each.

A.6. 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. 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 block randomization into treatment and control groups, and informational treatment consisting of an email message about the climate benefits of daytime EV charging.

The experimental schedule of the spring trial experiment is documented in Figure A2. 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' EVs. These data allow for estimates of total charging activity.

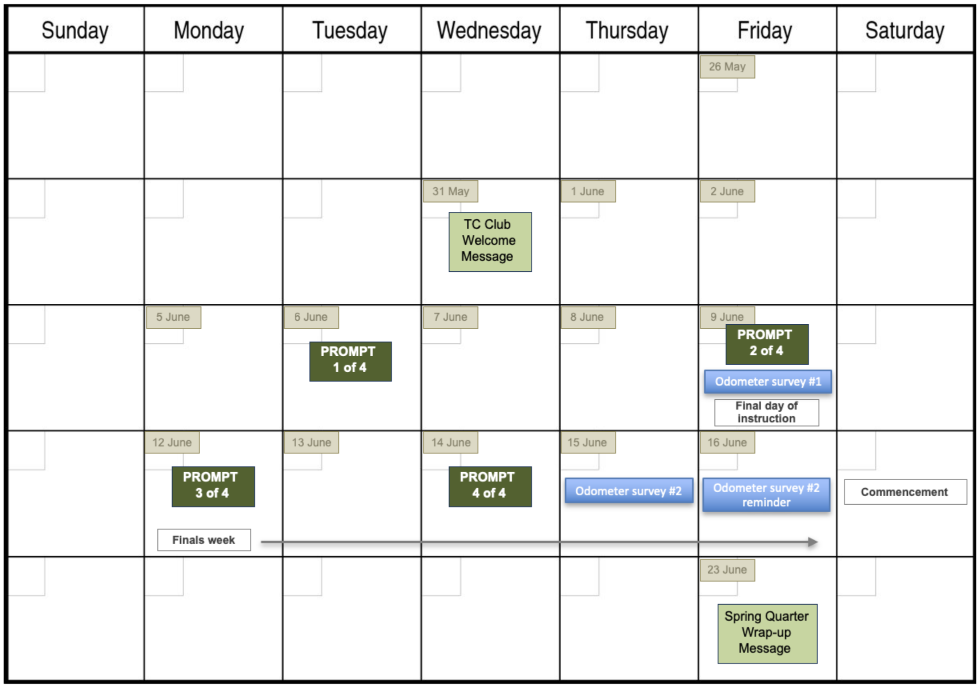


Figure A4: Experimental schedule for the spring trial experiment

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.

A.7. Clean Air Day

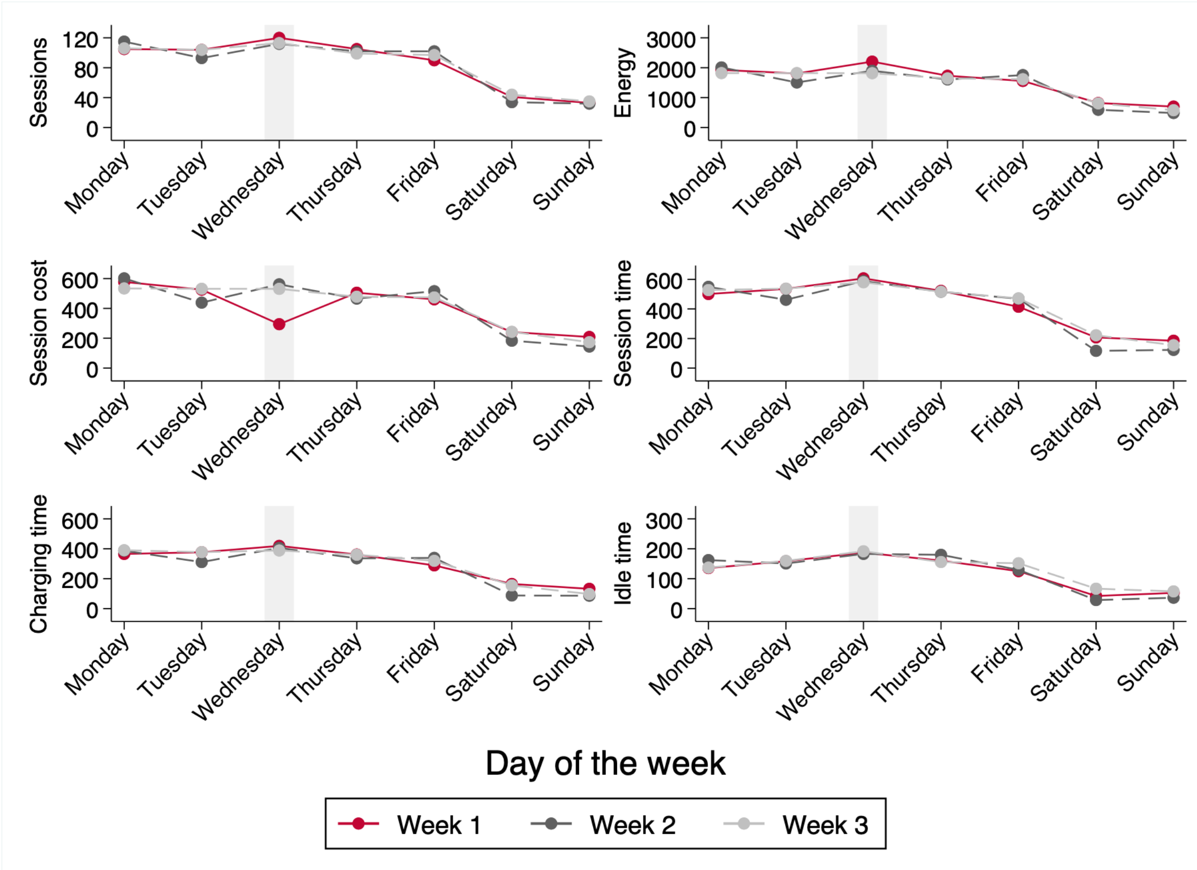


Figure A5: Charging activity around Clean Air Day by day of the week

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); 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). Weeks 1 to 3 correspond to October 2-8 (red), October 9-15 (gray), and October 16-22 (light gray). Clean Air Day was 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.

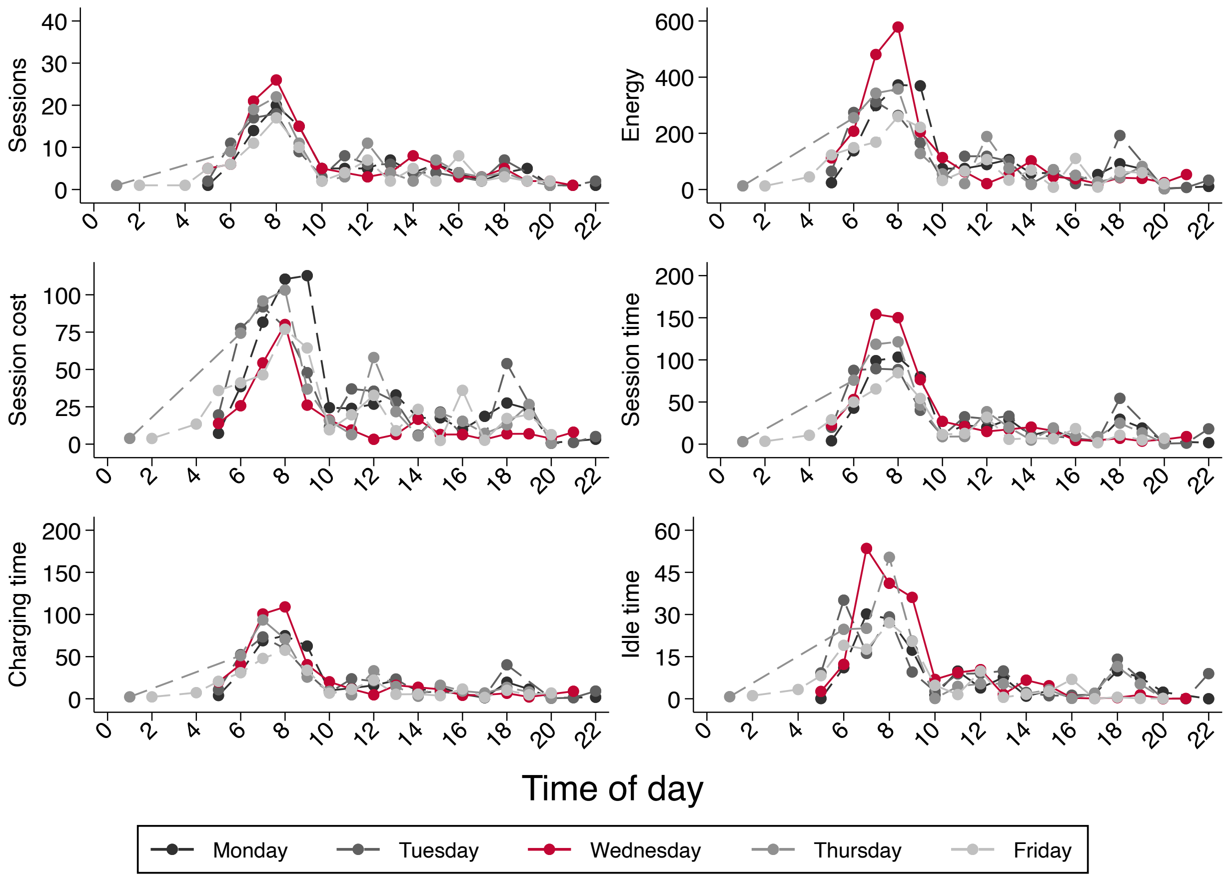


Figure A6: Charging activity around Clean Air Day by time of day

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 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). Clean Air Day (denoted in red) was Wednesday, October 4. "Session duration" denotes the full plug-in duration; "charging duration" the duration of active charging; and "idle duration" the duration parked but not charging.

A.8. Charger scarcity experiment

Four months after our series of informational and financial experiments, we ran a follow-up intervention over 13 days from February 5 to 17 to test for incentive-induced perceptions of scarcity of available chargers. In this intervention, we varied the discount notifications such that the messages to treated and control groups implied that different numbers of drivers would receive the discount. This follow-up experiment mimicked phase 1 of the financial experiment: the same methodology, same participants (i.e., new club enrollees were excluded), stratified block randomization into treatment arms that receive small or large discounts, notifications, and odometer surveys. The experimental schedule of the follow-up scarcity experiment is documented in FigureA7.

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

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

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

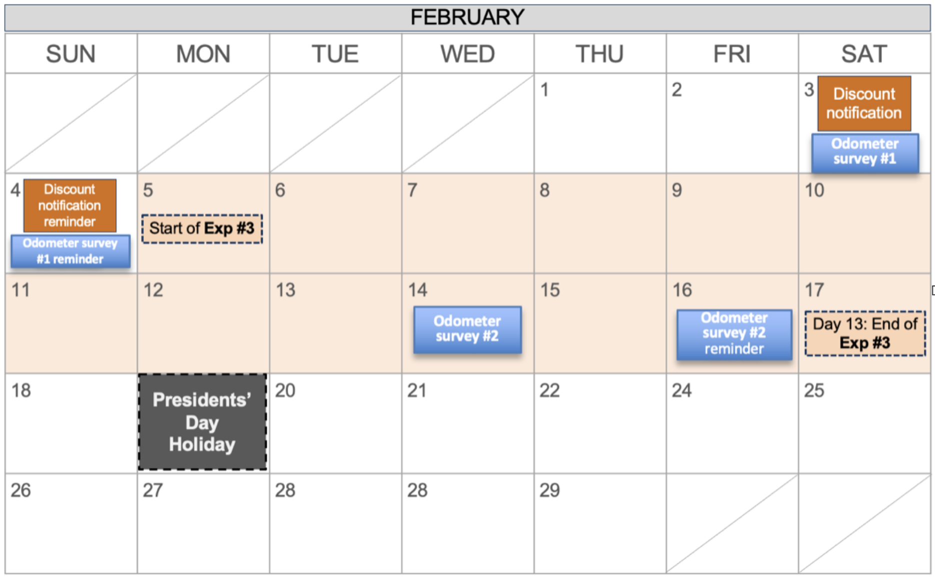


Figure A7: Experimental schedule for the scarcity experiment

Notes: This figure shows the schedule of the charger scarcity experiment (February 5 to 17). The experiment consists of two treatment arms: a financial and an induced scarcity intervention. During the financial treatment, participants receive either a small or large discount on workplace charging. During the scarcity intervention, participants were told either that no more than 33% of the club or generically that Triton Chargers would receive the discounts.

B. Supplementary network information

This Section provides additional information about the UCSD EV charging stations (Section B.1), SDG&E EV charging rates (Section B.2), UCSD network operation (Section B.3), UCSD network utilization (SectionB.4), and UCSD network reliability (Section B.5).

B.1. UCSD EV charging stations

UCSD has installed three distinct types of EV parking stalls across its campus (Figure B1) that differ in charger type and parking rules:

1. EV-1 indicates a 1-hour parking limit at a DC fast charger 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. 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. 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. Parking is free for the first 30 minutes, $4.20 per hour with a daily maximum of $33.60, and $2.10 per hour after 5 pm on weekdays and on weekends with a maximum of $8.40. 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.

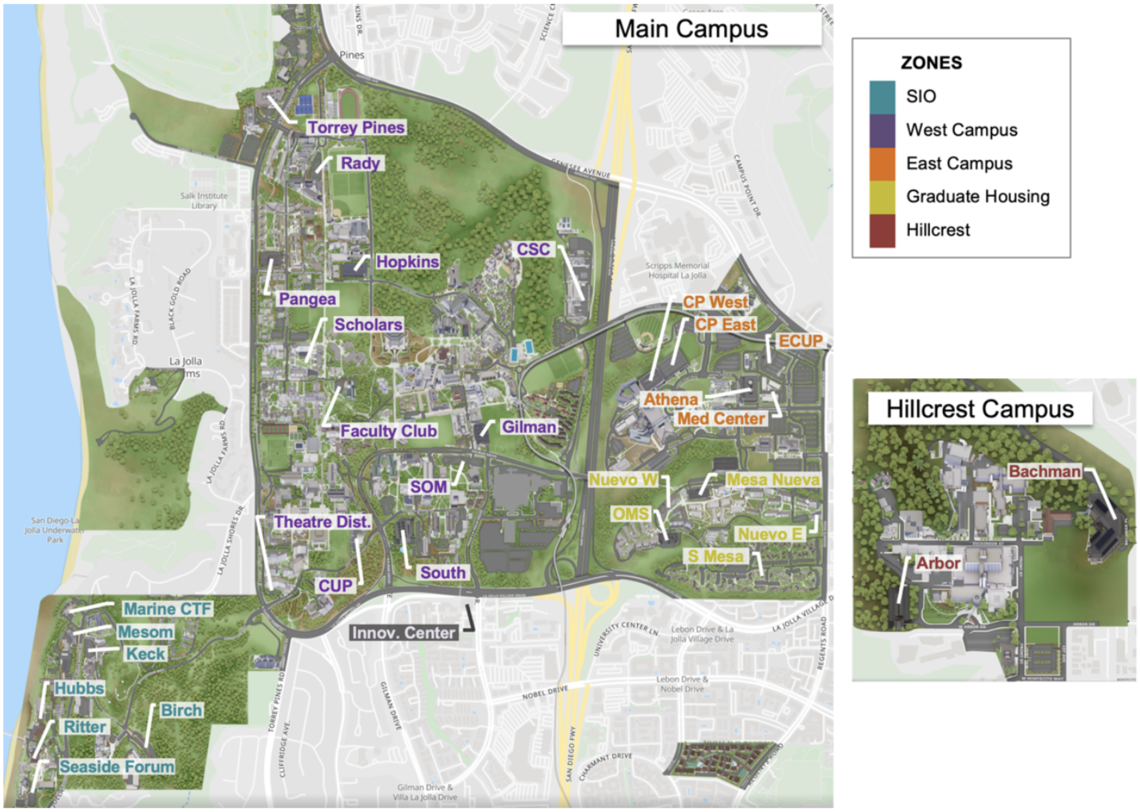


Figure B1: Parking zones and plazas at UCSD

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

B.2. SDG&E EV charging rates

Table B1: 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.

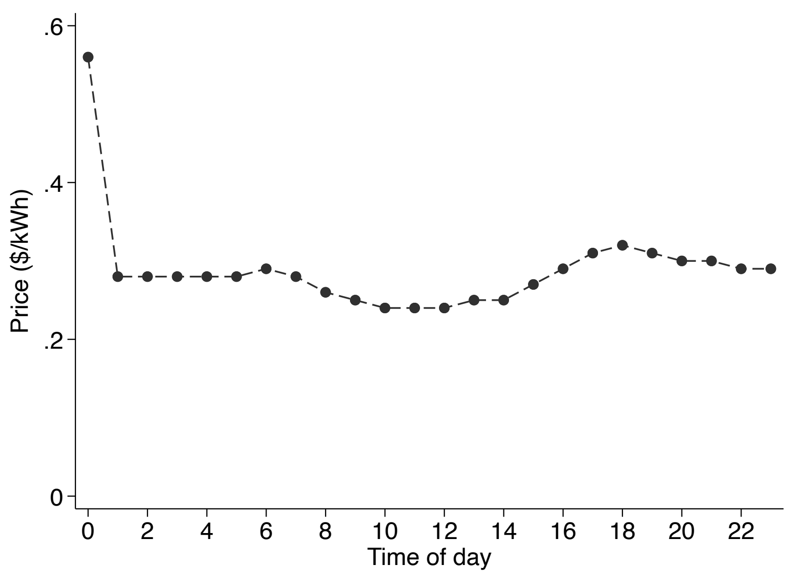


Figure B2: SDG&E public retail EV charging rates

Notes: This figure plots the mean hourly prices for SDGE's Power Your Drive public charging program during our intervention period (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. UCSD network operation

To calculate the daily "effective" network utilization that drivers experience at work, we classify chargers daily as either operational, non-operational, or out-of-service (Figure B3). A charger is "operational" if it reported at least one successful charging session on a given day. A charger is "non-operational" if it exclusively recorded glitch sessions (i.e., those that last fewer than five minutes or supply fewer than .5 kWh of energy). A charge is "out-of-service" if it reports ten or more successive days without activity. For shorter durations without activity, if either the most recent or following day with activity saw a successful session, the charger is operational. If both these days saw only glitches, the charger is non-operational.

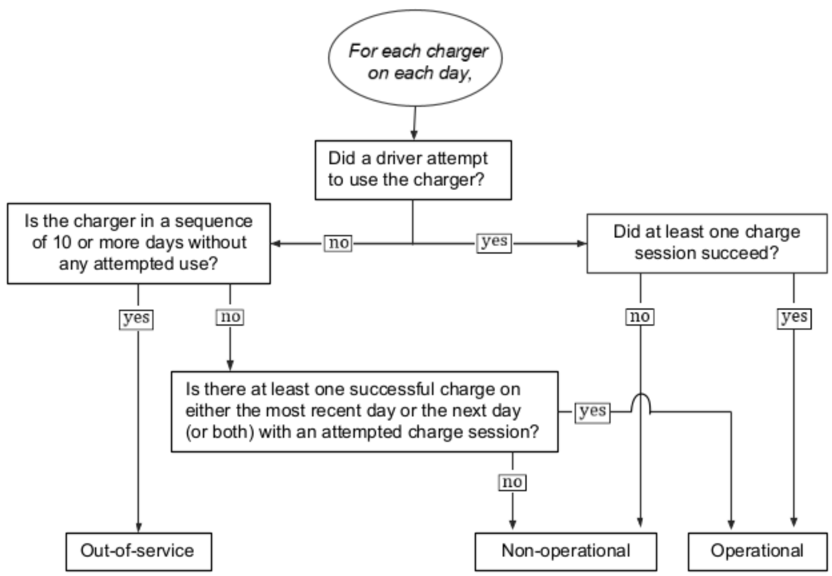


Figure B3: Network operation flowchart

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

Figures B4 and B5 report charger designations by day for PowerFlex and ChargePoint, respectively, during the study period (October 5 – November 19). PowerFlex chargers show variability across parking garages. The Athena parking structure rarely has more than one non-operational station and none out-of-service. In contrast, a few charge ports in the Gilman and Hopkins parking structures were mostly non-operational. Similarly for ChargePoint garages, the Gilman chargers show a relatively high non-operational frequency and a larger share of chargers overall reported no charge attempts.

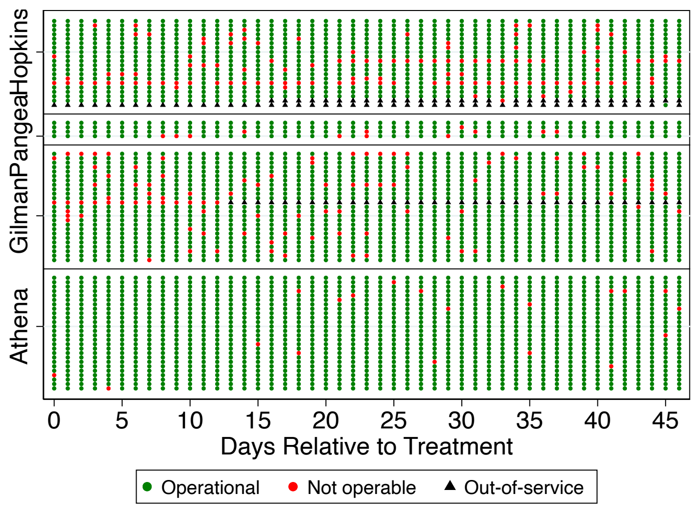


Figure B4: PowerFlex charger designation by day

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

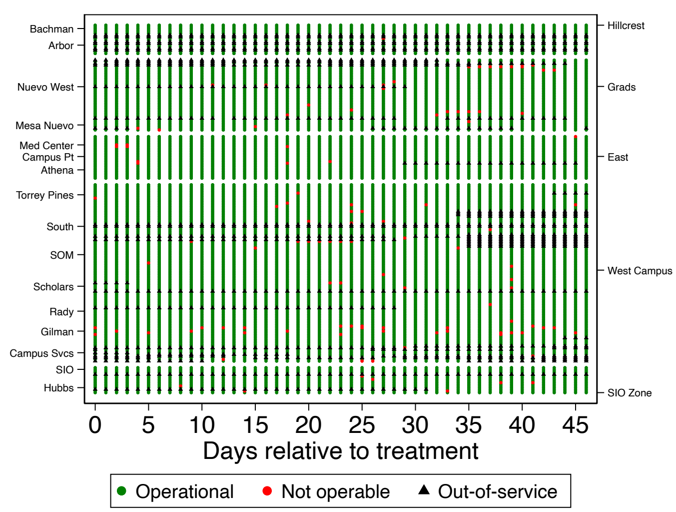


Figure B5: ChargePoint charger designation by day

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

Figure B6 reports the network-wide share of PowerFlex and ChargePoint chargers that were operational, non-operational, or out-of-service during the study period. For PowerFlex, non-operational and out-of-service chargers compose about 10% and 2% of total chargers; about 90% were thus operational. For ChargePoint, we observe higher out-of-service rate and more moderate non-operational frequency; roughly 86% of ChargePoint ports were operational on any given day. These estimates of network congestion represent a lower bound because they neglect "stall-napping"—occasions when vehicles occupy a charging stall without actually charging yet reduce charger availability all the same.

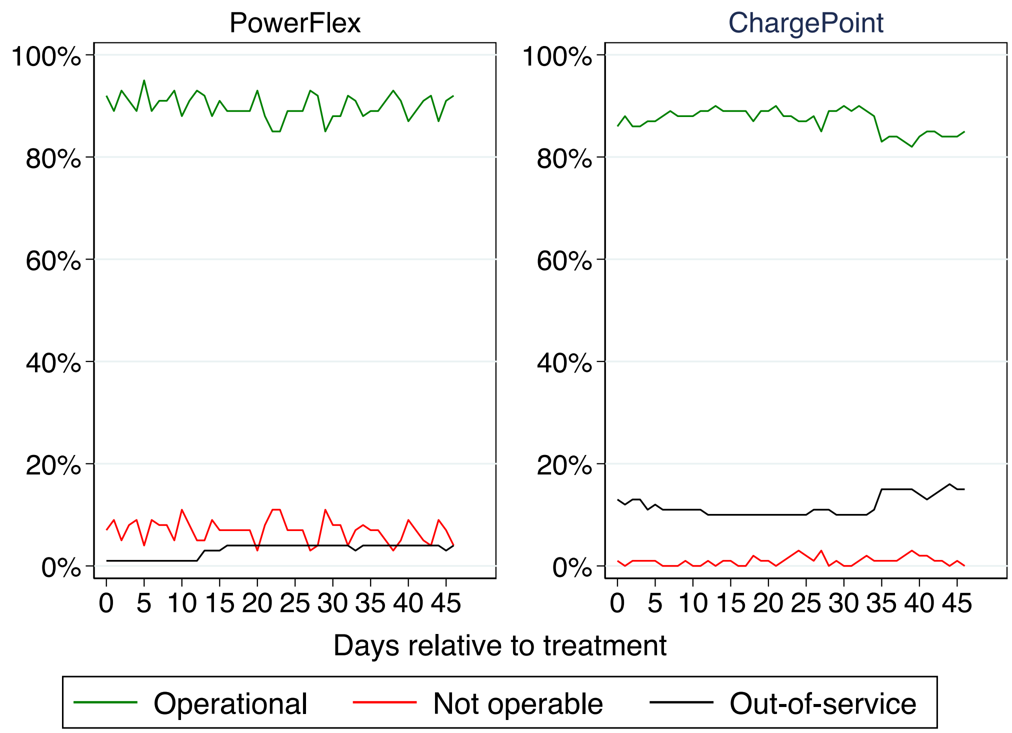


Figure B6: Charge port designation share

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

B.4. UCSD network utilization

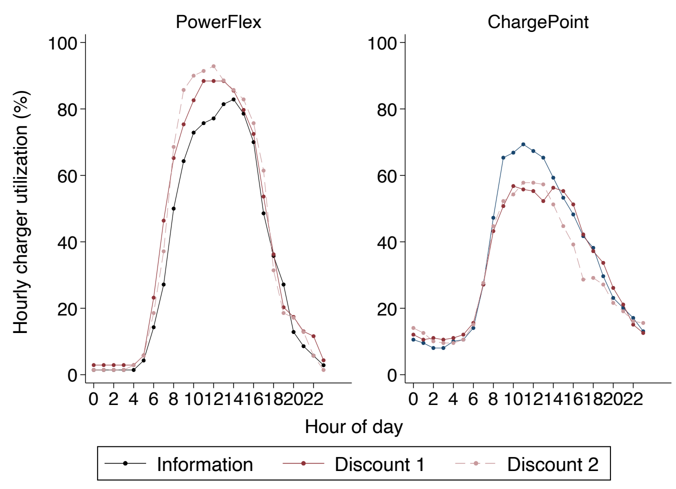


Figure B7: Monday's utilization by time of day and vendor

Notes: This figure shows hourly utilization of PowerFlex and ChargePoint chargers for the first Monday of the informational (October 9), first financial (October 30), and second financial treatment (November 13). 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 5 - November 19).

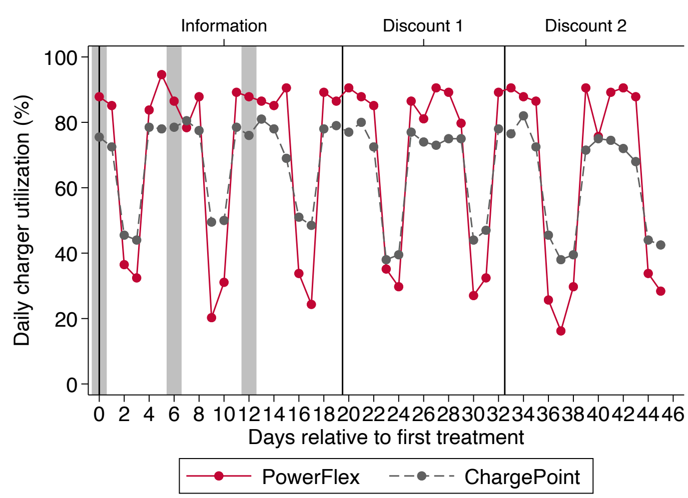


Figure B8: Network utilization by day

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 5 - November 19). 100 indicates that all chargers were used at least once during that day. Vertical dashed lines denote the start of each intervention; thick gray lines denote days on which the informational prompt was sent. We exclude chargers that are non-operational and out-of-service from the network utilization (Appendix B.3).

B.5. UCSD network reliability

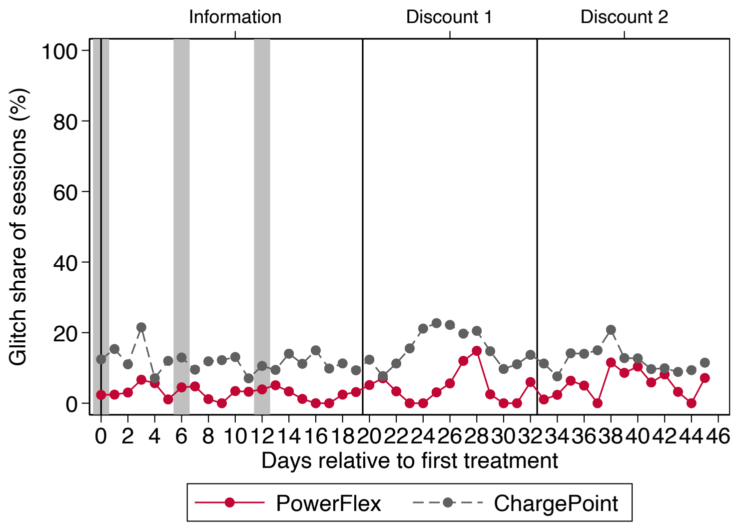


Figure B9: Charging session glitch rate

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

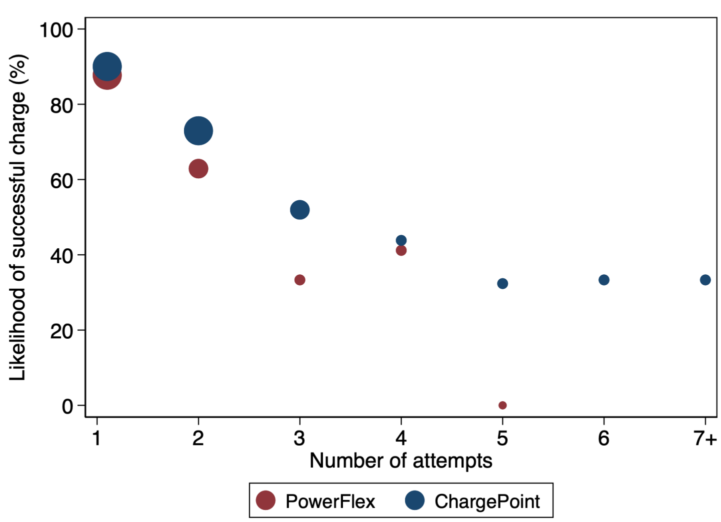


Figure B10: Probability of workplace charging by attempts

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

C. Additional results

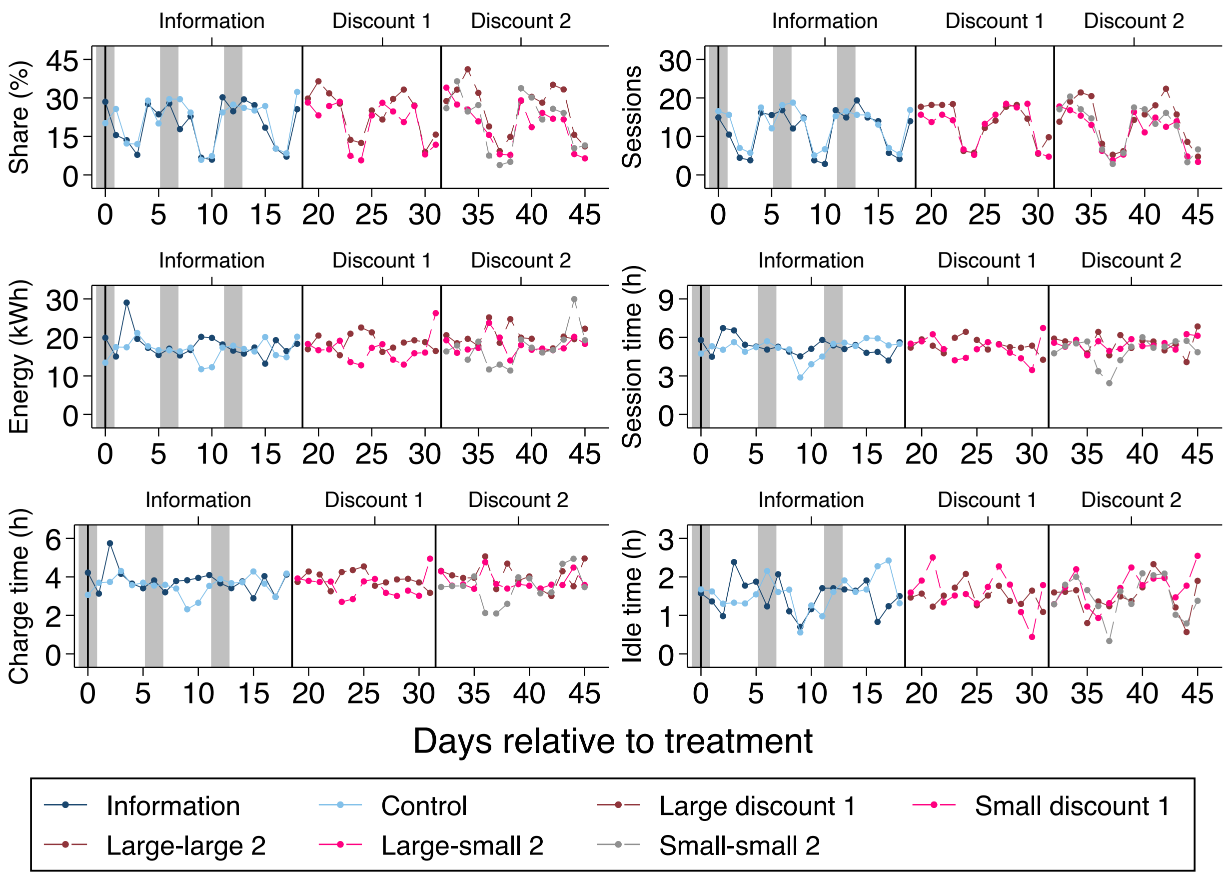


Figure C1: Total charging behavior by day

Notes: This figure shows the total charging activity by treatment and control group. Shown are the share of workplace charging (Panel A); number of charging sessions (Panel B); total energy consumed, in kWh (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 5). Dashed vertical lines denote the start of the informational (Day 0), first financial (Day 19), and second financial treatment (Day 32). Gray vertical bars denote the days on which information prompts were sent.

Table C1: Effect on the timing without charging restrictions

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Information	-.047*	.100*	-.041	-.025	-.015
	(.028)	(.057)	(.045)	(.034)	(.014)
Weekly plug-ins per driver	.07	.36	.28	.15	.04
B. Discount 1	.044*	.002	-.014	-.027	.038**
	(.023)	(.061)	(.050)	(.040)	(.017)
Weekly plug-ins per driver	.07	.41	.29	.15	.04
C. Discount 2	-.034	-.015	.043	.104*	.015
	(.037)	(.062)	(.057)	(.053)	(.025)
Weekly plug-ins per driver	.09	.36	.25	.15	.05

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

Table C2: Effect on the timing of charging with brand fixed effects

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Information	-.059*	.102*	-.026	-.017	-.009
	(.030)	(.059)	(.045)	(.030)	(.011)
Weekly plug-ins per driver	.07	.35	.27	.14	.04
B. Discount 1	.041*	-.021	-.024	-.024	.032*
	(.023)	(.060)	(.048)	(.036)	(.017)
Weekly plug-ins per driver	.07	.41	.28	.14	.04
C. Discount 2	-.035	-.064	.048	.100**	.022
	(.034)	(.062)	(.062)	(.050)	(.029)
Weekly plug-ins per driver	.09	.36	.31	.14	.05

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) excluding couples. The outcome variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment, first financial treatment, and interaction effect are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, as well as garage-fixed and vehicle-fixed effects. All coefficients are reported in individual×week. The weekly number of initiated charging sessions per driver is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C3: Effect on the timing of charging by week

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Week 1	-.036	.100	-.039	-.042	-.006
	(.031)	(.067)	(.053)	(.037)	(.010)
Week 2	-.046	.097	-.019	-.026	-.005
	(.034)	(.078)	(.060)	(.044)	(.020)
Week 3	-.069**	.100	-.045	.009	-.014
	(.034)	(.061)	(.061)	(.041)	(.021)
B.Discount 1					
Week 1	.053***	.026	.014	-.029	.024
	(.021)	(.064)	(.044)	(.044)	(.019)
Week 2	.036	-.013	-.052	-.029	.040**
	(.035)	(.072)	(.074)	(.043)	(.017)
C.Discount 2					
Week 1	-.061	-.091	.066	.121*	.045
	(.043)	(.071)	(.068)	(.069)	(.032)
Week 2	-.002	.025	.037	.102*	.011
	(.037)	(.077)	(.076)	(.053)	(.041)

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) for each week of the treatment. The outcome variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, as well as garage-fixed effects. All coefficients are reported in individual×week. The weekly number of initiated charging sessions per driver is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C4: Effect on total charging behavior during spring trial

	Total charging behavior					
	(1) Share	(2) Sessions	(3) Energy	(4) Session time	(5) Charge time	(6) Idle time
A. Information	-3.922	-.139	-.767	-67.245*	-15.752	-51.493**
	(7.436)	(.101)	(1.798)	(36.886)	(23.541)	(21.143)
Weekly mean dep. var.	27.32	.77	13.15	257.08	170.68	86.4
Observations	158	838	838	838	838	838

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

Table C5: Effect on additional charging behavior

	Additional charging behavior			
	(1) Vehicle miles	(2) Total energy	(3) Weekend	(4) DC Fast Charger
A. Information	-60.091	-15.414	-.074	.048
	(73.884)	(17.710)	(.172)	(.270)
Weekly mean dep. var.	862.33	226.45	.61	.48
B. Discount 1	21.942	5.934	.467	-.036
	(44.777)	(10.808)	(.314)	(.254)
Weekly mean dep. var.	511.35	134.28	1.18	.3
C. Discount 2	59.023	18.710	.496	-.215
	(50.137)	(12.803)	(.502)	(.178)
Weekly mean dep. var.	511.35	134.81	1.48	.23

Notes: This table presents the regression estimates of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) for additional charging outcomes. The first two outcome variables for drivers who responded to recurring odometer readings indicate the miles traveled during the intervention period (column 1), and the total energy dispensed for all charging sessions (column 2). The subsequent outcome variables indicate the total energy consumed on weekends (column 3), and the total energy consumed by DC Fast Charger (column 4). The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. The weekly 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.

Table C6: Effect on average charging behavior

	Average charging behavior			
	(1) Energy	(2) Session time	(3) Charge time	(4) Idle time
A. Information	-.236	-3.971	-2.810	-1.162
	(.661)	(10.709)	(8.222)	(5.017)
Mean per charge session	6.71	116.85	84	32.85
B. Discount 1	2.114***	24.867**	25.168***	-.299
	(.720)	(11.097)	(8.642)	(5.413)
Mean per charge session	7.94	132.59	98.07	34.53
C. Discount 2	.163	12.337	2.557	9.785
	(.965)	(13.852)	(10.721)	(6.877)
Mean per charge session	8.46	139.77	99.88	39.9

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 session duration, in minutes (column 2); average charging duration (column 3); and average idle duration (column 4). The informational treatment, first financial treatment, and interaction effect are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. Robust standard errors, clustered by individuals, are in parentheses. All coefficients are reported in individual×week. The mean outcome variable per charge session is reported below the coefficients. The number of observations is reported in the last row. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C7: Effect on the timing of charging by environmental motivation

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Informational prompt					
High Environmental Motivation	-.069*	.089	-.133	.065	.012
	(.042)	(.109)	(.094)	(.111)	(.028)
Low Environmental Motivation	-.049*	.100*	-.023	-.029	-.011
	(.029)	(.058)	(.045)	(.031)	(.012)
B.Financial incentive 1					
High Environmental Motivation	.049*	.074	.051	-.024	.036
	(.027)	(.143)	(.143)	(.063)	(.039)
Low Environmental Motivation	.044*	-.001	-.026	-.030	.032*
	(.023)	(.061)	(.049)	(.040)	(.017)
C.Financial incentive 2					
High Environmental Motivation	.002	-.033	.026	.039	-.046
	(.073)	(.194)	(.142)	(.077)	(.074)
Low Environmental Motivation	-.039	-.025	.059	.120**	.036
	(.035)	(.064)	(.065)	(.055)	(.036)

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 at work. 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 variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C8: Effect on the timing of charging by second discount groups

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
C.Discount 2					
Large-large vs. Large-small	-.035	-.026	.056	.112**	.028
	(.035)	(.063)	(.061)	(.053)	(.030)
Large-large vs. Small-small	-.034	-.037	.050	.109**	.028
	(.035)	(.065)	(.061)	(.050)	(.030)
Large-small vs. Small-small	-.001	.011	.006	.003	0

Notes: This table presents the regression estimates for the time of day in which sessions are initiated comparing the LL sequence to the LS and SS sequence during the second financial treatment (Panel C) using equation (2). The implied difference between the Large-small and the Small-small sequence is reported beneath the coefficients. The outcome variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, as well as garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C9: Effect on total charging behavior by week

	Total charging behavior				
	(1) Sessions	(2) Energy	(3) Session time	(4) Charge time	(5) Idle time
A.Information					
Week 1	-.022	-.073	-14.380	-3.276	-11.088
	(.102)	(1.980)	(35.388)	(26.000)	(16.072)
Week 2	.001	.404	2.191	7.744	-5.556
	(.120)	(2.224)	(40.309)	(29.016)	(19.867)
Week 3	-.020	-2.704	-47.596	-34.010	-13.598
	(.100)	(2.166)	(41.656)	(29.005)	(19.644)
B.Discount 1					
Week 1	.088	4.455**	47.190	53.608**	-6.424
	(.098)	(1.973)	(35.355)	(24.629)	(17.805)
Week 2	-.018	2.744	21.856	28.685	-6.424
	(.119)	(2.283)	(40.459)	(28.150)	(17.805)
C.Discount 2					
Week 1	.092	1.950	29.997	27.331	2.691
	(.127)	(2.900)	(44.745)	(33.169)	(17.630)
Week 2	.152	1.711	35.993	19.708	16.289
	(.142)	(2.610)	(47.581)	(33.529)	(22.860)

Notes: This table presents the regression estimates of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) for each week of the treatment. The outcome variables indicate the number of charging sessions (column 1); total energy consumed, in kWh (column 2); session duration, in minutes (column 3); charging duration, in minutes (column 4); and idle duration, in minutes (column 5). The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C10: Effect on the timing of charging by affiliation

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Non-Commuting Student	-.002	.320***	.003	-.079	-.050
	(.028)	(.089)	(.204)	(.135)	(.104)
Commuting Student	-.057**	.057	.019	.083	-.017
	(.028)	(.103)	(.098)	(.078)	(.015)
Faculty	-.045	-.119	-.115	-.111**	.023
	(.035)	(.082)	(.071)	(.048)	(.018)
Staff	-.055	.149**	-.020	.001	-.006
	(.042)	(.074)	(.054)	(.031)	(.010)
B. Discount 1					
Non-Commuting Student	.006	-.181	-.137	.044	.070
	(.025)	(.148)	(.161)	(.126)	(.114)
Commuting Student	-.001	-.151	.157	.054	.022
	(.032)	(.098)	(.102)	(.080)	(.019)
Faculty	.046	-.103	-.104	-.072	-.006
	(.035)	(.090)	(.080)	(.056)	(.016)
Staff	.045	.119	-.031	-.063	.040**
	(.029)	(.076)	(.054)	(.045)	(.017)
C. Discount 2					
Non-Commuting Student	-.030	-.038	-.036	.023	.184
	(.036)	(.124)	(.152)	(.216)	(.268)
Commuting Student	-.037	-.091	.069	.305**	.023
	(.030)	(.119)	(.170)	(.143)	(.043)
Faculty	-.016	.016	.287**	-.030	.008
	(.045)	(.135)	(.119)	(.058)	(.028)
Staff	-.039	-.012	-.020	.088	.001
	(.056)	(.087)	(.070)	(.055)	(.019)

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) by affiliation. The outcome variables indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment, and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, as well as garage-fixed effects. All coefficients are reported in individual×week. The weekly number of initiated charging sessions per driver is reported beneath the coefficients. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C11: Effect on the timing of charging by location

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
SIO	.012	-.060	.025	.030	.005
	(.013)	(.051)	(.037)	(.027)	(.005)
West Campus	-.102	.723*	.109	-.170	-.098
	(.125)	(.410)	(.216)	(.151)	(.117)
East Campus	-.549	.032	-.055	-.085	-.026
	(.365)	(.326)	(.085)	(.241)	(.033)
Graduate Housing	-.102	.112*	-.123	-.044	-.062
	(.116)	(.068)	(.185)	(.040)	(.040)
B.Discount 1					
SIO	-.012	-.108*	-.029	-.011	.000
	(.019)	(.058)	(.024)	(.024)	(.)
West Campus	-.065	.145	.093	-.075	.028
	(.154)	(.390)	(.173)	(.114)	(.071)
East Campus	.539***	-.068	-.005	-.197	.056*
	(.189)	(.232)	(.076)	(.324)	(.030)
Graduate Housing	.000	.053	-.281	.019	.155
	(.)	(.105)	(.182)	(.046)	(.132)
C.Discount 2					
SIO	.000	-.015	.003	.000	.000
	(.)	(.033)	(.002)	(.)	(.)
West Campus	-.136	-.263	.093	.344*	.107
	(.174)	(.371)	(.233)	(.187)	(.093)
East Campus	.056	-.160	.046	.349*	.000
	(.334)	(.226)	(.057)	(.206)	(.)
Graduate Housing	.080	.132	.031	.068	.204
	(.055)	(.114)	(.061)	(.072)	(.244)

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 campus location. The outcome variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C12: Effect on total charging behavior by scarcity

	Total charging behavior					
	(1) Share	(2) Sessions	(3) Energy	(4) Session time	(5) Charge time	(6) Idle time
A. Induced scarcity	-1.579	.063	.172	1.933	7.610	-5.686
	(2.667)	(.074)	(1.437)	(25.304)	(17.890)	(12.832)
B. Discount	-.870	.093	2.634*	40.674	18.982	21.691
	(2.644)	(.070)	(1.497)	(25.837)	(17.915)	(14.876)
C. Scarcity x large discount	-3.357	.082	1.955	19.377	21.324	-1.958
	(2.850)	(.091)	(1.715)	(29.404)	(20.592)	(14.223)
Weekly mean dep. var.	32.84	.85	15.39	274.32	196.54	77.77

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

Table C13: Effect on the timing of charging by network utilization

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Low Network Utilization	-.067	.287**	-.038	-.030	-.030
	(.049)	(.126)	(.118)	(.057)	(.026)
Medium Network Utilization	.045	.083	-.262	-.186	-.009
	(.043)	(.240)	(.197)	(.172)	(.053)
High Network Utilization	-.162*	.005	.004	.050	.012
	(.097)	(.156)	(.093)	(.088)	(.022)
B.Discount 1					
Low Network Utilization	.064*	.088	-.234*	-.087	.016
	(.033)	(.132)	(.136)	(.079)	(.042)
Medium Network Utilization	.034	-.352	.033	.009	.160***
	(.075)	(.218)	(.218)	(.155)	(.060)
High Network Utilization	.090	.046	.122	-.022	.055*
	(.079)	(.177)	(.106)	(.127)	(.028)
C.Discount 2					
Low Network Utilization	.025	-.110	-.034	.095	.097
	(.037)	(.148)	(.142)	(.076)	(.087)
Medium Network Utilization	-.029	-.103	.135	.336	.020
	(.061)	(.253)	(.354)	(.298)	(.129)
High Network Utilization	-.177	.060	.163*	.201*	-.014
	(.138)	(.188)	(.094)	(.104)	(.025)

Notes: This table presents the regression estimates on the timing of charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by network utilization. We define low, medium, and high utilization garages as garages with $\leq 60\%$, $60-75\%$, and $\geq 75\%$ utilization during the morning commute period ($7-12$ pm). The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual$\times$week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C14: Effect on the timing of charging by charger reliability

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Low Glitch Rate	-.067	-.021	-.122	-.026	.019
	(.064)	(.145)	(.133)	(.071)	(.024)
Medium Glitch Rate	-.097	.054	-.059	-.078	-.040
	(.080)	(.143)	(.116)	(.108)	(.034)
High Glitch Rate	-.064	.560***	-.001	.037	-.005
	(.060)	(.202)	(.134)	(.085)	(.023)
B.Discount 1					
Low Glitch Rate	.058	.001	-.293*	.005	.113**
	(.059)	(.155)	(.156)	(.079)	(.055)
Medium Glitch Rate	.134***	-.023	.100	-.017	.068***
	(.048)	(.157)	(.126)	(.132)	(.024)
High Glitch Rate	-.025	-.008	.086	-.171	-.048
	(.085)	(.204)	(.131)	(.111)	(.042)
C.Discount 2					
Low Glitch Rate	-.067	-.111	.032	.169*	.094
	(.066)	(.183)	(.168)	(.089)	(.091)
Medium Glitch Rate	-.024	-.105	.171	.318**	.015
	(.083)	(.144)	(.161)	(.155)	(.058)
High Glitch Rate	-.119	.203	-.081	-.100	.002
	(.141)	(.240)	(.159)	(.080)	(.044)

Notes: This table presents the regression estimates on the timing of charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by the glitch rates of the charger. We classify drivers' modal garage as having low, medium, or high glitch rates if the share of failed sessions is $\leq$ 10%, 10–20%, and $\geq$ 20%, respectively. The outcome variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual$\times$week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C15: Effect on the timing of charging by commute frequency

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Infrequent Commute	-.036	.045	.020	-.013	-.015
	(.026)	(.060)	(.054)	(.039)	(.021)
Frequent Commute	-.058*	.125*	-.060	-.023	-.005
	(.032)	(.072)	(.057)	(.042)	(.010)
B.Discount 1					
Infrequent Commute	.009	-.025	.046	-.063	.020
	(.024)	(.073)	(.067)	(.041)	(.020)
Frequent Commute	.063**	.022	-.053	-.012	.039**
	(.029)	(.075)	(.058)	(.050)	(.019)
C.Discount 2					
Infrequent Commute	-.033	-.082	.019	.004	-.005
	(.028)	(.078)	(.070)	(.080)	(.048)
Frequent Commute	-.035	.004	.076	.169**	.046
	(.050)	(.084)	(.084)	(.066)	(.032)

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

Table C16: Effect on total charging behavior by commute frequency

	Total charging behavior					
	(1) Share	(2) Sessions	(3) Energy	(4) Session time	(5) Charge Time	(6) Idle Time
A.Information						
Infrequent Commute	-4.440	.001	-1.789	-50.305	-19.639	-30.672**
	(5.658)	(.102)	(2.150)	(36.260)	(26.999)	(15.096)
Frequent Commute	5.693	-.021	-.310	-5.292	-5.130	-.159
	(4.599)	(.109)	(2.022)	(39.618)	(27.398)	(19.878)
B.Discount 1						
Infrequent Commute	1.248	-.012	.984	-16.432	.394	-16.823
	(5.168)	(.120)	(2.421)	(39.073)	(28.317)	(17.227)
Frequent Commute	.130	.060	4.945**	60.726	62.104**	-1.368
	(4.436)	(.114)	(2.312)	(42.333)	(30.216)	(21.327)
C.Discount 2						
Infrequent Commute	-11.063**	-.122	-3.182	-26.884	-40.713	13.841
	(5.373)	(.154)	(2.819)	(42.982)	(34.104)	(18.251)
Frequent Commute	2.547	.257*	4.347	66.210	58.002	8.220
	(5.006)	(.147)	(3.080)	(56.985)	(39.147)	(26.225)

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 frequency. An infrequent commuter comes to work less than three times; a frequent commuter three or more times. The outcome variables indicate the share of workplace charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session duration, in minutes (column 4); charging duration (column 5); and idle duration (column 6). The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C17: Effect on the timing of charging by access to home charger

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Home Charger	-.039	.088	-.016	-.048	-.013
	(.039)	(.071)	(.057)	(.030)	(.013)
No Home Charger	-.068**	.115	-.060	.021	-.001
	(.033)	(.083)	(.076)	(.069)	(.020)
B.Discount 1					
Home Charger	.043	.041	.006	-.028	.020
	(.031)	(.078)	(.061)	(.047)	(.020)
No Home Charger	.048	-.043	-.054	-.031	.050**
	(.032)	(.096)	(.085)	(.064)	(.024)
C.Discount 2					
Home Charger	-.015	-.112	-.022	.059	.050
	(.047)	(.082)	(.061)	(.044)	(.044)
No Home Charger	-.063	.102	.171	.189*	-.003
	(.040)	(.104)	(.114)	(.105)	(.040)

Notes: This table presents the regression estimates on the timing of charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by access to homer charger. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C18: Effect on the timing of charging by typical charging rate paid

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A.Information					
Low Charge Rate	-.030	-.034	.052	-.081**	-.008
	(.031)	(.058)	(.072)	(.040)	(.012)
Medium Charge Rate	-.032	.135*	-.029	-.023	-.014
	(.033)	(.069)	(.054)	(.038)	(.013)
High Charge Rate	-.118***	.134	-.131	.050	.006
	(.040)	(.105)	(.081)	(.062)	(.030)
B.Discount 1					
Low Charge Rate	.035	-.099	-.082	-.063	.005
	(.038)	(.100)	(.066)	(.046)	(.016)
Medium Charge Rate	.047*	.015	.004	-.021	.022
	(.027)	(.066)	(.059)	(.043)	(.019)
High Charge Rate	.050	.103	-.023	-.017	.098**
	(.064)	(.120)	(.085)	(.074)	(.039)
C.Discount 2					
Low Charge Rate	-.006	-.159	-.007	.051	.013
	(.046)	(.102)	(.084)	(.047)	(.030)
Medium Charge Rate	-.057	-.036	.116	.115	.044
	(.035)	(.071)	(.081)	(.072)	(.044)
High Charge Rate	-.001	.148	-.054	.169*	-.001
	(.094)	(.154)	(.087)	(.100)	(.038)

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 variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C19: Effect on the timing of charging by vehicle type

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Information					
Battery Electric	-.061*	.081	-.047	-.012	-.003
	(.032)	(.057)	(.049)	(.030)	(.011)
Plug-in Hybrid	-.016	.156	.006	-.044	-.024
	(.047)	(.135)	(.103)	(.091)	(.035)
B. Discount 1					
Battery Electric	.049**	-.015	-.021	-.030	.041**
	(.023)	(.063)	(.054)	(.040)	(.018)
Plug-in Hybrid	.029	.083	-.013	-.025	-.000
	(.057)	(.150)	(.124)	(.107)	(.028)
C.Discount 2					
Battery Electric	-.032	-.016	.046	.129***	.045
	(.042)	(.069)	(.060)	(.044)	(.033)
Plug-in Hybrid	-.042	-.056	.089	.059	-.024
	(.058)	(.165)	(.153)	(.149)	(.061)

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 variable indicate the number of initiated charging sessions during early morning (5:00 - 6:59) (column 1), morning (7:00 - 9:59) (column 2), midday (10:00 - 15:59) (column 3), evening (16:00 - 20:59) (column 4), and overnight (21:00 - 4:59) (column 5) periods. The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual×week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table C20: Effect on total charging behavior by typical charging rate paid

	Total charging behavior					
	(1) Share	(2) Sessions	(3) Energy	(4) Session time	(5) Charge Time	(6) Idle Time
A.Information						
Low Charge Rate	.756	-.102	.096	-31.450	-16.422	-15.024
	(6.161)	(.112)	(2.793)	(40.948)	(31.829)	(16.999)
Medium Charge Rate	3.416	.036	-.639	-10.529	-1.747	-8.785
	(4.217)	(.104)	(1.967)	(38.236)	(27.536)	(18.843)
High Charge Rate	.674	-.059	-2.045	-33.427	-24.724	-8.701
	(8.694)	(.159)	(3.019)	(55.638)	(38.741)	(24.909)
B.Discount 1						
Low Charge Rate	-5.265	-.204	-2.099	-39.088	-26.607	-12.469
	(5.183)	(.146)	(2.325)	(45.893)	(30.325)	(24.530)
Medium Charge Rate	.812	.067	4.033**	50.638	53.123**	-2.477
	(4.226)	(.103)	(2.035)	(38.184)	(26.796)	(19.516)
High Charge Rate	6.366	.211	8.883**	67.423	81.032*	-13.614
	(7.119)	(.188)	(3.811)	(67.290)	(45.507)	(31.529)
C.Discount 2						
Low Charge Rate	-4.571	-.087	-3.137	-41.894	-42.342	.458
	(5.217)	(.157)	(2.769)	(54.731)	(34.031)	(30.255)
Medium Charge Rate	-1.335	.162	1.390	34.738	29.261	5.494
	(5.012)	(.149)	(3.039)	(49.618)	(38.848)	(20.454)
High Charge Rate	-.763	.250	8.069	113.930	79.455	34.477
	(7.353)	(.204)	(5.473)	(92.143)	(63.348)	(37.865)

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, $\geq$\$.17/kWh and $<$\$.23/kWh; and high rates, $\geq$\$.23/kWh. The outcome variables indicate the share of workplace charging, by kWh (column 1); number of charging sessions (column 2); total energy consumed, in kWh (column 3); session duration, in minutes (column 4); charging duration (column 5); and idle duration (column 6). The informational treatment and first financial treatment are estimated using equation (1), while the second financial treatment is estimated using equation (2). All regressions include individual demographic, vehicle, charging infrastructure, motivational control variables, and garage-fixed effects. All coefficients are reported in individual$\times$week. Robust standard errors, clustered by individuals, are in parentheses. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D. Details of calculating the effect from charging

In this Section, we provide additional details to derive the annual social CO_2 emission damages (Section D.1), and LCFS revenues from EV charging (Section D.2).

D.1. Deriving emissions costs

We estimate the annual social CO_2 emission damages of workplace charging as the product of annual hourly energy consumed at work E_h, the hourly carbon intensity CI_h, and the SCC as follows:

$$CO_2^{work} = \sum_{h=1}^{24} E_h \cdot CI_h \cdot SCC. \tag{D1}$$

Using the driver's share of energy charged at work (Table 1) allows us to back out the estimated energy consumption from home charging. We define the share of charging at work as the total energy consumed from workplace charging divided by the expected energy consumed from total driving, which we estimate from the driver's miles traveled and their vehicle's energy efficiency. Multiplying the energy of home charging by the carbon intensity of the average charging profile of Triton Charger EV club members $\overline{CI}$ gives us the annual CO_2 emissions from home charging:

$$CO_2^{home} = \frac{\sum_{h=1}^{24} E_h}{Share_E^{work}} \cdot (1 - Share_E^{work}) \cdot \overline{CI} \cdot SCC. \tag{D2}$$

D.2. LCFS revenues

Equation (D3) illustrates the change in LCFS revenues that result from the temporal shifts in workplace charging, which is equal to the product of the change in electricity consumption by hour and the carbon intensity of electricity at that hour:[41]

$$\triangle LCFS_h^{timing} = \sum_{h=1}^{24} (CI_{standard} - \frac{CI_h}{3.4}) \underbrace{(\beta_h^{kWh} + \delta_{1h}^{kWh} + \delta_{2h}^{kWh})}_{Timing\ work\ charging} \cdot \bar{P} \cdot 3.4, \tag{D3}$$

where $CI_{standard} = 89.5\ gCO_2/MJ$ is the typical carbon intensity from gasoline-powered cars, and $\bar{P} = \$64.51\ /\ tCO_2$ 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.

[41] We treat the intervention implementation costs as a transfer from the institution to drivers receiving the discounts.