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

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Abstract

Synchronizing the timing of electric vehicle charging with abundance of renewable energy is critical to decarbonization of the transportation sector. In solar dominated grids, this means promoting daytime charging when vehicles are often in the workplace. In a field experiment, we find that pro-social environmental nudges increase charging during solar hours but not overall charging at the workplace. Price discounts increased workplace charging but during non-solar hours. We identify three mechanisms explaining these temporal shifts: the utilization and reliability of the network, concerns about charger scarcity, and driver characteristics. Finally, we assess the societal impacts of these shifts, including CO_2 emissions and marginal electricity costs.

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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). 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). Alongside the transition to EVs, most strategies for deep decarbonization anticipate a rapid uptake of renewable energy in the power sector (International Energy Agency, 2021), given that the carbon footprint associated with EV charging is contingent on the carbon intensity of the power grid. The efficacy of these strategies in achieving their objective of reducing emissions hinges on the charging behavior of drivers; charging affects both the power grid, which must accommodate increased demand, and emissions, given that marginal grid emissions fluctuate throughout the day (Imelda et al., 2022). In solar-dominant grids, this variation means that shifting to midday charging – when most people are at work – could potentially reduce carbon emissions.

Although most charging today is done at home — enabled because early EV adopters tend to be wealthier and have higher rates of homeownership (LaMonaca & Ryan, 2022) — workplace charging remains crucially important for two reasons. First, future EV owners will likely have less access to private home charging and hence require alternative charging options (Chakraborty et al., 2019). Second, as the electric grid incorporates more intermittent renewable energy, the value of electricity storage[1] and flexible load options (like EV charging) will grow alongside the need to balance fluctuations in energy supply and demand (Holland et al., 2022; Powell et al., 2022). With many institutions committing to net-zero carbon goals and supporting their employees with charging facilities, the extent to which EVs reduce emissions will depend on how drivers interact with workplace EV networks and, in turn, how workplace policies influence their charging decisions.

Shifting future electricity demand from vehicle charging to midday is advantageous for climate mitigation for three reasons: First, there is an excess of solar generation. For instance, between December 2022 and November 2023, California curtailed 2.6 million MWh of renewable power (California Independent System Operator, 2024), mainly during midday, due to a lack of demand or storage — equivalent to energy for 35 million full charges of an

[1] Despite the growing capacity of grid-connected battery storage systems, shifting EV charging to daytime hours remains critical because current battery storage capacity and fossil fuel generation are insufficient to fully meet the increase in peak evening demand that widespread EV adoption could bring.

average EV and enough to charge 633,000 EVs over an entire year.[2] Scaled to the vehicle fleet in California (currently 25.6 million cars) and assuming that vehicles typically charge every four days, a standard throughput of 6 kW implies they could collectively draw 38.4 GW if plugged in simultaneously, exceeding typical peak demands and potentially offsetting the "duck curve" — the midday dip and evening surge in electricity demand — if charging is distributed more evenly throughout the daytime hours. Second, if charged during daytime instead of overnight, we calculate that California's current EV stock of 1.29 million vehicles would decrease annual emissions by an additional 1.35 million tCO_2 — equivalent to avoided global damages of \$252 million, assuming a social cost of carbon of 210 $\frac{\$}{tCO_2}$. Third, growing midday electricity demand (e.g., through EV charging) is likely to drive up wholesale electricity prices, enhancing revenue streams for merchant solar power plants.

In this paper, we run a series of interventions aimed at increasing workplace daytime charging and thereby reducing CO_2 emissions from charging. Our interventions include financial discounts for charging at work and environmental nudges that provide information on the benefits of workplace daytime charging. These interventions have been studied in the context of shifting the timing of home charging (Bailey et al., 2023; La Nauze et al., 2024; Burkhardt et al., 2023). However, in our context and in most solar rich states, we understand very little about shifting people's charging behavior to the workplace during working hours. Drivers have various charging options (at work, in public, or at home, if available) and charging habits that range from ingrained to flexible. We conducted a randomized controlled field experiment ($n = 629$) at the University of California San Diego (UCSD) — host to a large workplace EV charging network — to investigate how these interventions shape drivers' decisions to use workplace charging. Our research utilizes a newly established EV club for UCSD affiliates, explicitly created to advance research on EV charging behavior at the workplace. This EV club allowed us to collect comprehensive data on drivers' demographics, vehicles, commuting patterns, and workplace charging habits, representing the largest experimental basis of EV driver behavior to date.

Our experiment investigates how environmental nudges and financial incentives can induce a shift in *where* and *when* drivers charge. The experiment consists of two interventions conducted in sequence: an informational treatment from October 5 to 23, 2023, followed by two phases of financial treatment from October 24 to November 19. First, we provide drivers with information about the CO_2 emission benefits associated with daytime versus nighttime charging, delivered three times (once per week). Second, we give drivers discounts

[2] This calculation considers only battery EVs (not plug-in hybrids) and assumes mean vehicle performance (3.5 miles/kWh efficiency, 76 kWh battery size), 14,600 annual vehicle miles traveled, and mean overnight (22–6) and daytime (9–15) grid carbon intensities of 91.96 and 21.65 gCO_2/MJ, per CARB's 2023 LCFS emission attribution methodology that uses average emission factors.

on workplace charging, irrespective of time. We chose flat discount rates for workplace charging over time-of-day rates to address the key challenge of encouraging drivers to plug-in at work for two reasons: First, flat discount rates allow us to estimate the first-order question of how elastic drivers are in substituting their charging demand from non-workplace to workplace charging. Second, commercial EV charging technology, operated by large charging networks, is rapidly evolving to enable network operators to dynamically control charging flows. If incentives can effectively encourage drivers to plug-in at the workplace, particularly during daylight hours, automated algorithmic solutions could then manage the timing of charging to align with grid demands and reduce emissions.[3] Additionally, time-of-use pricing is likely to yield similar results, as most drivers typically plug in their vehicles before peak sunlight hours, limiting the potential impact of time-dependent incentives.

In the first phase of this financial treatment, participants receive either a small ($\$.16/kWh$) or large ($\$.23/kWh$) discount on the base workplace rate of $\$.30/kWh$, such that workplace charging is slightly cheaper than overnight home charging and equal to the average locational marginal price (LMP) of electricity (which is the lowest plausible cost that drivers could pay for charging), respectively.[4] In the second phase of financial treatment, we move half of the large discount group to the small discount while otherwise maintaining the first phase, allowing us to investigate habit formation for workplace charging.

Our key results report how the interventions influenced how much drivers charged and when they charged at work. We found that the environmental nudges had a small, negative effect on total workplace charging that was indistinguishable from zero. In contrast, the 50% discount on workplace charging resulted in a 21.8% increase in energy consumption, implying a price elasticity of workplace charging of $-.44$. To put this into context, the estimated off-peak price elasticity of EV charging is -1.59 (Bailey et al., 2023), suggesting that EV drivers are considerably less responsive to incentives for shifting charging from home to the workplace compared to adjusting the timing of their charging. However, as the charging behavior of drivers who received the large-small sequence of discounts reverted to those receiving the small-small sequence, our results suggest a lack of habit formation in drivers' charging behavior after the discount ended.

Our interventions also led to significant shifts in when drivers initiated charging sessions. We consider the timing of charging across five distinct windows: early morning (5–7),

[3]In the context of automated load management, the timing of when people physically plug in will matter less for total carbon emissions than the number of EVs plugged in during the day. While much research has focused on the technical potentials for automated load management (ALM) to optimize workplace EV networks (McClone et al., 2023), algorithmic solutions require that drivers first behave in preferred ways (i.e., be plugged-in at preferred times).

[4]For the remainder of the paper, we refer to the effect of financial incentives as the difference between receiving small and large discounts.

morning (7–10), midday (10–16), evening (16–21), and overnight (21–5). Receiving environmental information led to a reduction of .045 (5.3%) weekly early morning charging sessions and a shift to later morning charging, an intertemporal substitution toward daytime hours more aligned with solar generation. Conversely, the first discount on workplace charging led to an increase of .044 (4.3%) early morning and .031 (3.3%) weekly overnight charging sessions, while charging decreased during the rest of the day. Additionally, the second phase of the financial discount resulted in an increase of .118 (12.4%) weekly evening sessions but a smaller shift to early morning charging. This indicates an intertemporal substitution in the opposite direction, toward periods of lower network utilization but away from midday solar energy generation, a perverse effect in which financial incentives for charging increase CO_2 emissions.

An important attribute of EV charging at the workplace is the bundling of parking spots and chargers. Our setting reflects the likely trajectory of workplace charging infrastructure in other contexts at the forefront of EV adoption. Most planned infrastructure upgrades only include a subset of parking spots enabled with EV chargers (Badia et al., 2019). We find evidence to support at least three different mechanisms that can explain the temporal shifts in workplace charging: the quality of workplace charging infrastructure, the experimental incentive structure, and driver characteristics. First, 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 low 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.

Second, financial discounts may affect commuters' *perceptions* of charger availability. Within congested networks, discounts may instill the belief that drivers need to charge during periods when workplace chargers are less occupied to secure an available charger. We find support for this mechanism in a follow-up experiment with identical financial intervention as well as messaging designed to prime perceptions of such incentive-induced scarcity. Drivers primed to perceive high incentive-induced scarcity shifted from early morning to evening when the network is less utilized, highlighting that perceptions of scarcity alone shift charging behavior toward periods of lower utilization.

Third, we examine the relationship between several driver characteristics and their response to the interventions. As frequent commuters mainly shift to evening and overnight sessions during discount periods, greater commuting flexibility may allow drivers to adjust their charging schedules in response to incentives. Additionally, access to private home charging and low-cost overnight rates may influence the response in charging behavior: drivers without home chargers or facing high charging prices at their usual location significantly shift to evening and overnight sessions in response to financial incentives.

Finally, we calculate the societal benefits of these total and temporal shifts in charging, measured as avoided CO_2 emissions and changes in the cost of charging. Overall, the total and temporal shifts in workplace charging during the informational and the first financial treatment led to a net benefit of 1.16% and 1.21% in avoided CO_2 emission damages and reductions in the cost of charging, while the net effect of the second financial treatment was −1.95%. If scaled to all EV owners in California, the informational and first financial intervention would have decreased CO_2 emission damages by \$2.9 million and \$2.4 million annually, whereas the second financial intervention would have increased CO_2 emissions by \$3.7 million annually. The first financial discount would cost approximately \$6,230 per ton of avoided CO_2 emissions, indicating that financial demand-side interventions are a highly cost-ineffective policy for emission reduction in EV workplace charging. Conversely, environmental nudges may offer a more cost-efficient policy for reducing CO_2 emissions, contingent upon their financial costs. Across interventions, the charging-induced environmental effects are substantially larger than the marginal changes in participation in California's Low Carbon Fuel Standard (LCFS), highlighting the importance of factoring in emission damages when setting EV charging rates.

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 rates of homeownership (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 exist no experimental evidence on how to induce a shift to daytime workplace charging.[5] Our workplace-wide experiment marks the first effort to deliver evidence on micro-level charging behavior at the workplace and constitutes the

[5]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., 2023). Informational interventions have also proven effective, including information on estimated cost savings (Nicolson et al., 2017), on charging sourced from renewable energy (Nienhueser & Qiu, 2016), and tailored at the point of charge (Asensio et al., 2021).

largest experimental study for workplace EV research.[6]

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 exceed available chargers — as a central impediment to shifting drivers to daytime workplace charging.[7] 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.[8]

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,[9] we derive an empirical framework that allows us to estimate the emission damages and the marginal cost of supplying electricity for EV charging from the effect of our interventions. Our framework characterizes how shifts in the workplace charging usage and timing alter CO_2 emissions and the cost of charging. Finally, we also derive the financial implication 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 summarizes data. Section III provides the empirical methodology, experimental findings, and mechanisms. Section IV discusses the societal and institutional implications of the experiment. Section V concludes with policy implications.

[6] Although the literature lacks an experimental basis around workplace EV charging, there are a 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).

[7] 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).

[8] 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).

[9] 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).

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 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).[10] 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 recruitmentof 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.

[10]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.

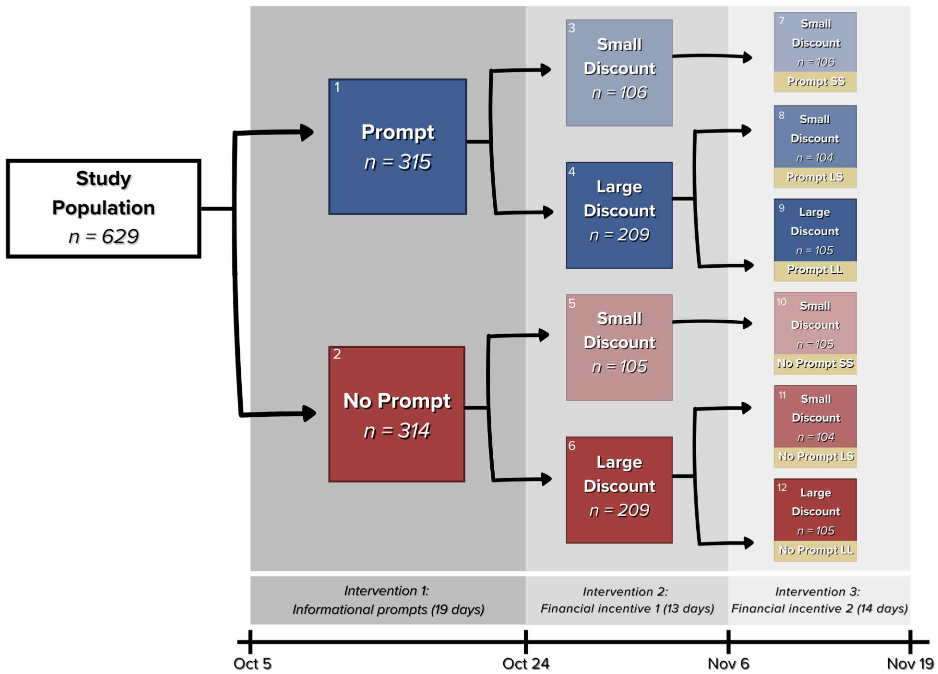


Figure 1: Experimental design

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.[11] 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.[12] 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 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

[11]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.

[12]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).

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.[13] 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.[14] 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.[15] 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 parking rules (i.e., exceed 16 hours).[16] Appendix B.1provides information on chargers and parking rules at UCSD.

[13] 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.

[14] 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.

[15] Some sessions in our dataset are fragmented, potentially due to software resets, driver actions such as unplugging and replu gging, 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.

[16] 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).

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),[17] 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). We supplement our dataset with the LMP of electricity from California's Independent System Operator (2023) (CAISO) to estimate the change in electricity cost of charging due to charging at locations associated with different LMPs.

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%).[18] The average EV is 2.4 years old and has been driven 29,153 miles; 76% of EVs in our study are battery-electric. The mean daily driving mileage is 40 miles, and the mean one-way commute distance is 14 miles. 59% of participants report having a home charger. Drivers report paying, on average, $\$.18/kWh$, although 190 participants

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

[18] 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.

(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):

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

where i indexes the driver; y_i refers to the charging outcome variable of interest; $Info_i$ and $Reward_{1i}$ are dummy variables equal to 1 if the individual received the informational prompts and large discount in the first financial treatment, and equal to 0 otherwise; the vector X_i represents a rich set of individual socio-demographic variables, vehicle characteristics, charging attributes, and motivation about charging;[19] and α_j are garage-fixed effects (i.e., modal charging location) to control for time-invariant charging characteristics. The coefficients of interest β and δ measure the effect of the information and financial treatment on the outcome of interest. The coefficient η measures the interaction effect between informational and financial treatment.

For the second phase of the financial experiment, we consider an analogous specification

[19] Socio-demographic control variables include age, gender, income, years of education, weekly days commuting to work, commuting distance, and a dummy variable for affiliation. Vehicle characteristics and charging attributes include vehicle age, 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.

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.

to that in equation (1), but we replace the $Reward_{1i}$ dummy with an indicator variable $Reward_{2i}$ denoting 1 if an individual is in the large discount group in the second phase. To estimate habit formation, we restrict our sample to drivers who received the first financial discount and compare the charging behavior of those who continued receiving large discounts to those who reverted to small discounts in the second phase. In addition, we control for the total energy and charging sessions during the five distinct time periods on Veterans Day (November 10). Standard errors are clustered at the individual-level.

We use the model specification in (1) 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 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

[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).

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 from a similar, smaller trial experiment we ran in June 2023 (Table C3). 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 3.2 kWh in total weekly energy consumption.[22] Relative to the weekly average of energy dispensed at the workplace, $E^{work}_{small} = 14.66$ kWh, this corresponds to an 21.8% increase in total 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

[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 after the experiment (Table C2).

[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).

for workplace charging, as given by:

$$\sigma = \frac{\frac{\Delta E^{work}}{E^{work}}}{\frac{\Delta P^{work}}{P^{work}}} = \frac{\frac{E^{work}_{large} - E^{work}_{small}}{E^{work}_{small}}}{\frac{P^{work}_{large} - P^{work}_{small}}{P^{work}_{small}}} = \frac{21.8\%}{-50\%} \approx -.44 \tag{2}$$

The estimated price elasticity of workplace charging therefore equals $-.44$. 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) in Bailey et al. (2023), 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 C4), 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 higher average energy consumption and longer charging duration per session, which suggests that the larger discounts are associated with longer sessions (Table C5).[23] 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. This is consistent with the slight increase in energy 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).

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 change individuals' total charging activity. This is also reflected in the weekly mean share of charging done at work, which decreased from 33% to 29% across the first and second financial treatment. 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.

[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	2.892	-.009	-.185	-15.505	-4.836	-10.667
	(3.186)	(.086)	(1.645)	(31.345)	(22.401)	(15.055)
Weekly mean dep. var.	28.44	.85	14.55	268.07	187.17	80.9
B. Discount 1	-.463	.012	3.205*	28.877	35.878	-6.996
	(3.623)	(.095)	(1.829)	(33.236)	(22.727)	(17.323)
Weekly mean dep. var.	32.93	.93	16.48	294.69	209.1	85.59
C. Discount 2	-1.632	.123	1.916	33.081	23.960	9.137
	(4.622)	(.121)	(2.500)	(42.238)	(30.651)	(18.398)
Weekly mean dep. var.	28.95	.87	16.19	285.02	199.93	85.09
D. Information x large discount	-1.858	-.000	.295	-17.419	-4.478	-12.939
	(3.163)	(.088)	(1.592)	(30.874)	(21.394)	(15.697)
Observations	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). 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.

2. *Effect on the timing of charging behavior* Next, we transition to temporal shifts in charging behavior. Figure A3 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 substantial decrease in charging sessions initiated between 5–7 am and a slight increase in initiated sessions between 7–10 am (Panel A). In addition, we observe a reduction in initiated sessions between 3–9 pm. Conversely, the first financial intervention shifts charging to 5 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. The informational treatment resulted in a significant decrease of .045 weekly early morning charging sessions (5–7), which was compensated by an (insignificant) increase in sessions during the morning (7–10). Given an average of .85 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.[25]

[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.

[25]Consistent with the idea that environmental motivation is a determinant of EV charging timing, we find

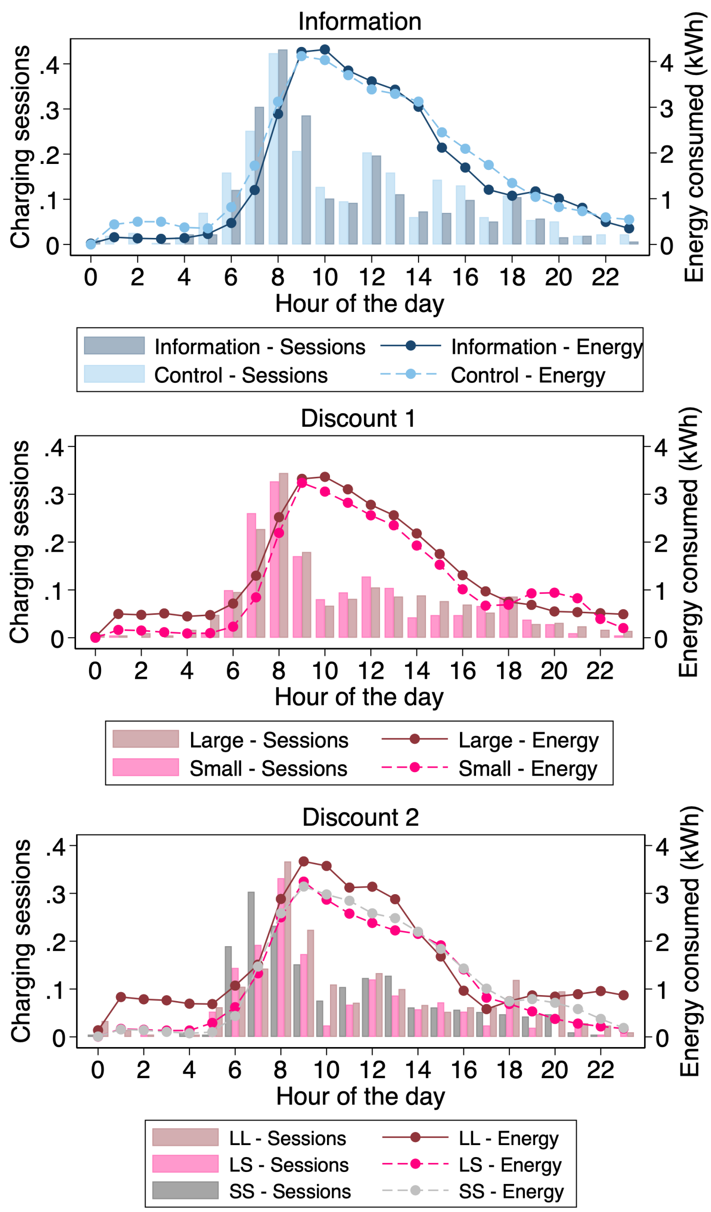


Figure 2: Number of charging sessions and energy consumed by hour of the day

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.

Conversely, the first financial discount for workplace charging yielded a significant increase of .044 early morning (5-7) and .031 overnight sessions (21-5) and an (insignificant) decrease in initiated charging sessions over the rest of the day. This corresponds to a shift of 4.3% and 3.3% of the weekly workplace charging sessions per driver due to the first financial incentive. 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, drivers who continued receiving large discounts in the second phase (LL) significantly increased evening sessions (16–21) by .118 (12.4%) compared to those who were switched to small discounts (LS). As the timing of initiated charging sessions of drivers who received reduced discounts reverted to those receiving the small-small sequence of discounts (Table C7), 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 C2) and total energy consumed (Table C8) solely in the first week of the first financial intervention

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 C4). Moreover, we document that the estimated coefficients are robust to including vehicle-brand-fixed effects in addition to the vehicle characteristics and garage-fixed effects (Table C9). We also verify that the experimental results are robust to including baseline charging controls (Table C10).

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 early morning and overnight charging as a response to financial discounts (Table C6).

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	-.045*	.087	-.024	-.019	-.008
	(.027)	(.056)	(.044)	(.032)	(.011)
Weekly plug-ins per driver	.07	.35	.26	.13	.03
B. Discount 1	.044**	.001	-.028	-.035	.031*
	(.022)	(.061)	(.048)	(.040)	(.017)
Weekly plug-ins per driver	.07	.41	.27	.14	.04
C. Discount 2	-.045	-.023	.055	.118**	.025
	(.035)	(.067)	(.064)	(.054)	(.029)
Weekly plug-ins per driver	.09	.36	.31	.14	.05
D. Information x large discount	-.028	.060	-.008	-.024	-.001
	(.022)	(.059)	(.043)	(.037)	(.011)
Observations	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. 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.

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 "quality" (i.e., reliability and availability) of workplace charging infrastructure, the effect of experimental incentives on perceptions of charger scarcity at work, 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, 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.[26] Second, 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. 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. *Quality of charging infrastructure.* We test two charging network attributes that plausibly affect drivers' charging decisions. The first is high network utilization, defined as the fraction of chargers used during a given hour, which could discourage drivers from charging 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.[27] 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 (Figure 4a). In response to informational prompts, the drivers who shift to later morning

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

[27] 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.

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.[28] 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).

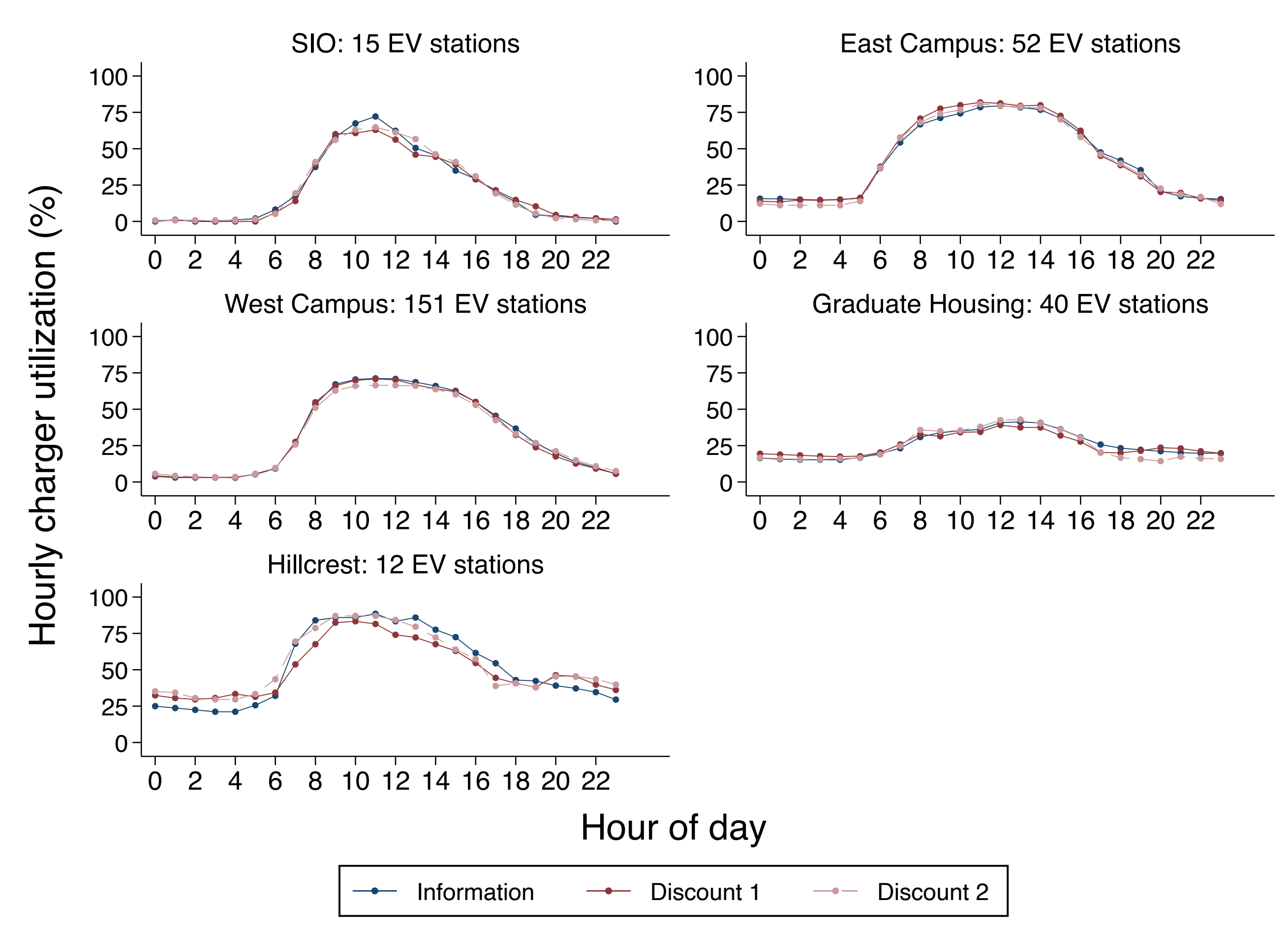


Figure 3: Network utilization by time of day and campus zone

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.

[28] 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.

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).[29] Moreover, drivers who unsuccessfully plug in on their initial attempt are less likely to receive a charge during immediately consecutive attempts (Figure B10).

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 reliable, drivers who charge at low-glitch-rate garages lead most temporal shifts in charging during all interventions (Figure 4b).[30]

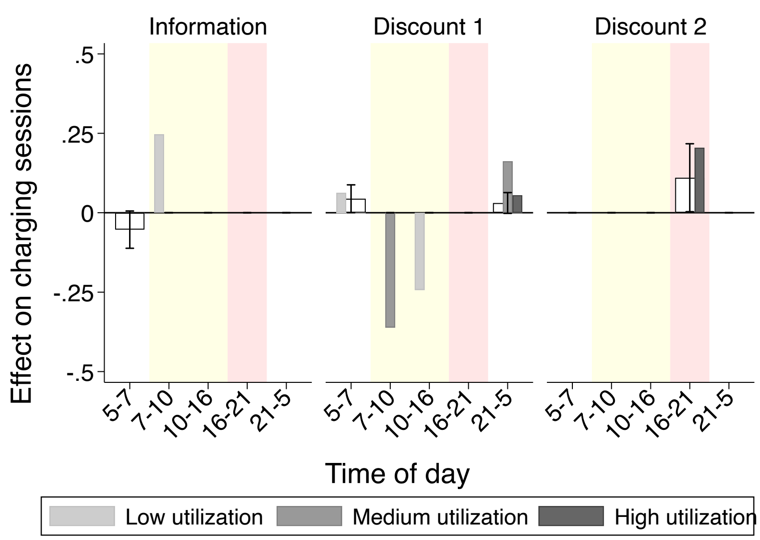
2. *Experimental incentive structure.* In addition to the quality of network infrastructure, financial discounts themselves could increase drivers' perceptions of scarcity if drivers believe lower charging rates induce greater workplace-wide charging. Figure B7 suggests an almost 10% surge in hourly 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 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.

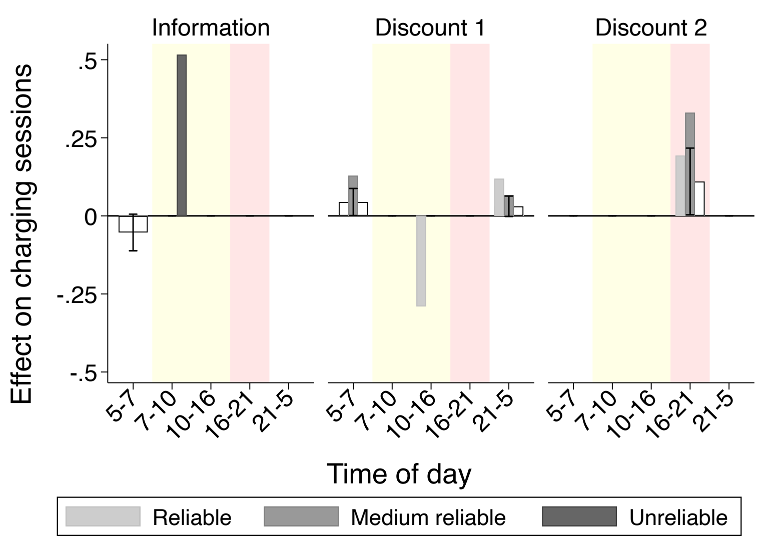
Expectations of incentive-induced scarcity resulted in a shift from early morning to late evening charging sessions equivalent to the transition from the first to the second financial

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

[30] 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.



(a) Network utilization



(b) Charger unreliability

Figure 4: Effect on the timing of charging by network infrastructure

Notes: This figure displays the significant regression estimates (hollow bar) for the time of day in which sessions are initiated across the informational (left), first financial (middle), and second financial treatment (right). We show significant treatment effects (solid bars) on the timing of charging sessions for two mechanisms: Network utilization (Panel a), and session glitch rate (Panel b). Morning and midday periods are associated with low grid carbon intensity (7 - 16; depicted in yellow), whereas evening periods typically exhibit higher carbon intensity (16 - 21; depicted in red). All coefficients are reported in individual×week. We set statistically insignificant estimates to 0. 95%-confidence intervals are indicated through whiskers and reflect robust standard errors.

discount intervention (Table C12). 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 nearly 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.[31] Thus, the incentive-induced perception of scarcity can explain some of our observed shifts during the financial intervention toward evening charging when the network is less congested.

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 (Figure C2a), 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 C14), 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 (Figure C2b) or those who report paying high modal prices for charging at their usual location (Table C15). 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.[32] 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 C17),which suggests that financial interventions have a more pronounced effect on these commuters.

[31]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 C13).

[32]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 C16).

IV. Policy implications

A. Effects from EV charging

In this Section, we present an empirical framework for estimating the effects of our interventions on workplace charging usage and timing from societal and institutional perspectives.

1. *Societal effect.* From a societal perspective, the total and temporal effects of shifting workplace charging affected the global avoided CO_2 emission damages (denoted $\triangle CO_2$) and the total electricity cost of charging (denoted $\triangle LMP$). Although these effects benefit different groups — global benefits from CO_2 emissions reductions, and ratepayer benefits from lower electricity costs — we refer to the sum of these effects as the experiment's societal effect. Focusing on marginal changes in charging behavior induced during the information and financial treatments, the societal effect $\triangle E^{societal}$ is the sum of avoided CO_2 emissions and the changes in the electricity cost of charging per driver annually:

$$\triangle E^{societal} = \underbrace{\overbrace{\triangle CO_{2,h}^{timing} + \triangle CO_2^{location}}^{Global}}_{Effect\ on\ environment} + \underbrace{\overbrace{\triangle LMP_h^{timing} + \triangle LMP^{location}}^{Ratepayer}}_{Effect\ on\ electricity\ cost}. \tag{3}$$

Each effect involves changes in workplace charging due to shifts in the timing of workplace charging (denoted with superscript *timing*) and home charging, which result from a shift of charging from home to the workplace (denoted with superscript *location*).

To estimate the monetary implications of the change in CO_2 emissions, we calculate how our interventions affect commuters' charging-related CO_2 emissions.[33] 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.[34] Equation (4) displays the change in charging-related CO_2 emission from our interventions:

[33] 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.

[34] As our interventions did not significantly affect the total vehicle miles traveled or energy dispensed at work charging sessions for drivers who responded to recurring odometer readings (Table C4), 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).

$$\triangle CO_2 = \sum_{h=1}^{24} \underbrace{(\beta_h^{kWh} \cdot CI_h + \delta_{1h}^{kWh} \cdot CI_h + \delta_{2h}^{kWh} \cdot CI_h)}_{Timing\ work\ charging} \cdot\ SCC$$
$$- \underbrace{(\beta^{kWh} \cdot \overline{CI} + \delta_1^{kWh} \cdot \overline{CI} + \delta_2^{kWh} \cdot \overline{CI})}_{Shifts\ home\ charging} \cdot\ SCC, \tag{4}$$

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.[35] β^{kWh}, δ_1^{kWh}, and δ_2^{kWh} indicate how the informational, first financial, and second 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.[36] Multiplying this with the Environmental Protection Agency's social cost of carbon (SCC) of 210 $\frac{\$}{tCO_2}$ (2022) yields the total cost of CO_2 emissions.

In electricity markets, the LMP reflects the marginal cost of supplying the next increment of electricity demand at a specific location within the grid, considering three components: energy cost (i.e., cost of generating electricity at the cheapest marginal resource), congestion cost (i.e., cost associated with the capacity of the transmission network, which can prevent the cheapest electricity from reaching certain locations), and losses (i.e., cost due to the electrical losses that occur during transmission). The marginal cost of energy constitutes the primary component of LMP (Figure D1). Specifically, we measure how our interventions affect the electricity cost of charging as drivers shift from home to workplace charging (or vice versa), which are associated with different wholesale electricity prices (i.e., LMP) reported by CAISO pricing node.[37] Equation (5) shows the change in the marginal electricity costs that arise through the information and financial treatments:

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

[36]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).

[37]This relates to the literature on EVs impact on distribution grids, which indicates that capacity upgrades of 25 GW are necessary to accommodate the anticipated increase in electricity consumption in California (Li & Jenn, 2024).

$$\triangle LMP = \sum_{h=1}^{24} (\underbrace{\beta_h^{kWh} \cdot LMP_h + \delta_{1h}^{kWh} \cdot LMP_h + \delta_{2h}^{kWh} \cdot LMP_h}_{Timing\ work\ charging}) - (\underbrace{\beta^{kWh} \cdot \overline{LMP^{home}} + \delta_1^{kWh} \cdot \overline{LMP^{home}} + \delta_2^{kWh} \cdot \overline{LMP^{home}}}_{Shifts\ home\ charging}), \tag{5}$$

where LMP_h refers to the hourly LMP of electricity at UCSD's pricing node during the intervention period. $\overline{LMP^{home}}$ denotes the daily average LMP of electricity at our drivers' typical pricing node.[38]

2. *Institutional effect.* The institution that hosts the charging network can generate revenues from shifts in workplace charging usage and timing (denoted $\triangle LCFS_h^{timing}$) 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. Equation (6) 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:[39]

$$\triangle LCFS_h^{timing} = \sum_{h=1}^{24} (CI_{standard} - \frac{CI_h}{3.4}) (\underbrace{\beta_h^{kWh} + \delta_{1h}^{kWh} + \delta_{2h}^{kWh}}_{Timing\ work\ charging}) \cdot \bar{P} \cdot 3.4, \tag{6}$$

where $CI_{standard} = 89.5\ gCO_2/MJ$ is the typical carbon intensity from gasoline-powered cars, and $\bar{P} = \$64.51\ /\ tCO2$ 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. 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.

[38] We identified the ten zip codes with the most Triton Club members (representing nearly 50% of our sample) and matched these to the pricing nodes that serve these areas based on proximity (excluding those associated with UCSD's microgrid).

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

[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.

B. Mapping experimental results to theory

Table 4 summarizes the societal impact of avoided CO_2 emissions and changes in the societal cost of charging resulting from our interventions (equation 3). We report the societal effect comprising the weighted average of CO_2 emission damages and the LMP of electricity from charging (Appendix D.1). The social CO_2 emission damages and the marginal cost of supplying electricity for EV charging are equal to \$148.66 and \$147.58 per driver annually.

Panel A of Figure 5 shows the changes in hourly CO_2 emissions due to temporal shifts in workplace charging during the three interventions. The grid carbon intensity (grey dashed line) is typically low during midday but sharply increases during the evening as solar generation dissipates and rising demand mobilizes fossil-based power plants. The temporal shifts in workplace charging from the informational treatment reduced CO_2 emissions by 1.72% as drivers shift charging away to later morning periods. The first and second discounts increased emissions by 5.63% and 5.3% due to more frequent early morning and overnight charging hours with higher grid intensity.

Table 4: 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	1.72	−5.63	−5.3
Due to shift in home charging	−.24	6.89	3.4
Locational marginal price ($\triangle LMP$)			
Due to timing of work charging	1.06	−5.53	−5.3
Due to shift in home charging	−.23	6.7	3.3
Societal effect ($\triangle E^{societal}$)	1.16	1.21	−1.95

Notes: This table reports the societal effect measured as the percentage change in carbon emissions per equation (4) and electricity cost of charging 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 societal effect represents the weighted average change in carbon emissions and LMP. The effects associated with each discount period represent the impact of the large discount relative to the small discount levels.

The informational intervention reduced the energy consumed at work, while the financial incentives led to additional energy dispensed from workplace charging. As workplace charging has 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 .24%.[41] In contrast, the increase in total energy consumed at work during the financial discount periods led to a CO_2 reduction of 5.63% and 5.3%, respectively. Although financial incentives led to workplace charging during higher carbon intensity periods, the shift from 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 and first financial discount resulted in a CO_2 reduction of 1.48% and 1.26%, while the second financial treatment resulted in a CO_2 increase of 1.9%. If scaled to all EV owners in California, the informational treatment and first financial treatment would avoid \$2.9 million and \$2.4 million in CO_2 emission damages per year, whereas the second financial discount would inflict \$3.7 million in CO_2 emission damages. The first financial discount, at a cost of \$6,230 per ton of avoided CO_2 emissions, indicates 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 \$2.21 per driver assuming a SCC of \$210 per ton.

Panel B of Figure 5 shows the changes in the electricity cost of charging due to intertemporal shifts in charging during the three interventions. The LMP at UCSD's pricing node (grey dashed line) is typically high during evening periods, indicating no societal tradeoff in the optimal timing of EV charging between CO_2 emissions and the wholesale electricity costs, as both follow similar hourly cost patterns. The informational prompts reduced the cost of charging by 1.06% by shifting to daytime charging with abundant solar energy. In contrast, the discount-induced early morning and overnight charging sessions increased the cost of charging at UCSD by 5.53% and 5.3%. However, the overall shift in charging from home to work reduced the cost of charging at our driver's homes, resulting in total changes in the cost of charging of .83% during the informational period, 1.17% during the first financial discount, and −2% during the second financial discount.

From a societal perspective, the informational treatment led to a 1.16% increase in avoided CO_2 emissions and reduced cost of charging, which resulted from a shift to workplace charging with lower grid intensity. The net effect of the first financial treatment equals 1.21%, primarily due to shifting from home to work charging. However, as drivers shifted gradually to late evening charging hours with higher grid intensity and LMP and away-from-work charging, the net effect of the second financial treatment equals −1.95%.

[41] 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.

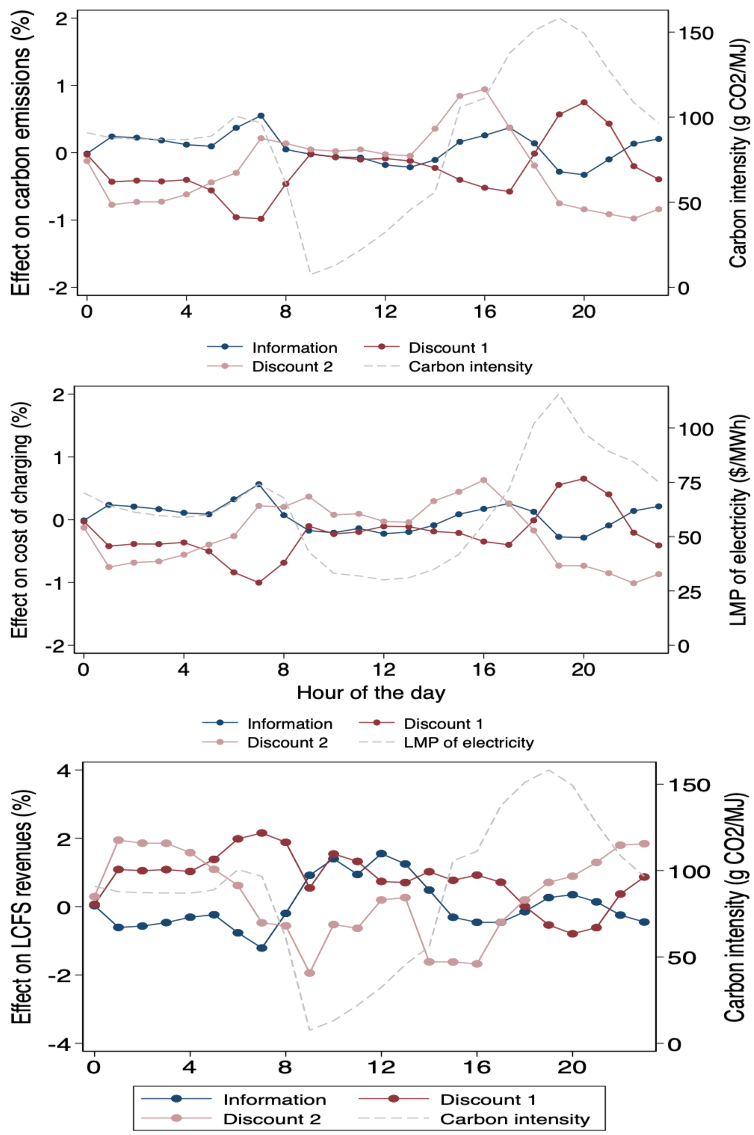


Figure 5: Effect on hourly CO_2 emissions, LMP of electricity, and LCFS revenues

Notes: The figure displays the percentage change in hourly carbon emissions (Panel A), electricity cost of charging (Panel B), and LCFS revenues (Panel C) due to the temporal shifts from EV workplace charging of each intervention. The grey dashed line in Panels A and C denotes the hourly carbon intensity from the California Air Resources Board in 2023-Q3. The grey dashed line in Panel B denotes the average marginal LMP of electricity at UCSD's pricing nodes during our intervention period from CAISO.

Panel C of Figure 5 shows the percentage change in LCFS revenues due to intertemporal shifts in charging during the three interventions. Compared to the $44.67 in LCFS revenue generated annually per driver from EV workplace charging, the financial incentives led to an increase of 19.33% and 6.95% in LCFS revenues for the institution that hosts the workplace charging, primarily due to the shift from home to workplace charging. 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 increased the institutions' LCFS revenues by .9% as drivers shifted to daytime charging hours with higher LCFS credits. From the perspective of UCSD, summed over all Triton Charger club members, the informational and the two financial interventions increased annual LCFS revenues by $254, $5,430, and $1,953, respectively.

1. *Distributional effects.* We contrast the revenues earned through California's LCFS program to the costs of providing drivers discounts on workplace charging (denoted $\triangle Costs$). The cost of implementing the intervention, per equation (7), is total energy consumed by each discount group throughout the experiment multiplied by the respective small ($\$.16/kWh$) and large ($\$.23/kWh$) discounts, applicable to all Level-2 workplace charging sessions:

$$\triangle Costs \ = (\underbrace{E_l \cdot \ \$.23/kWh)}_{Large\ discount} \ + \ \underbrace{E_s \cdot \ \$.16/kWh}_{Small\ discount}). \tag{7}$$

E_l and E_s refer to the total energy consumed by the large and small discount groups during the experiment. For the first financial treatment, the incentives paid to the average participant were $7.43 for the large and $4.36 for the small discount. For the second financial treatment, the average incentives provided to the participants came to $8.59 for the large and $4.54 for the small discount. Converted to an annual basis, the intervention implementation costs of these discounts substantially outweigh the charging-induced marginal changes in LCFS revenues from workplace EV charging per driver.

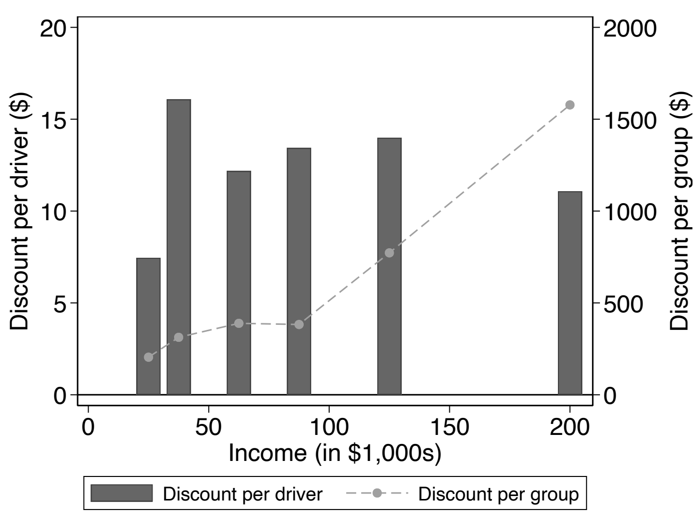


Figure 6: Discounts by income

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.

A common objection to providing financial incentives for charging is that the benefits accrue unevenly across socioeconomic groups. Figure 5 presents the distributional profile of the financial discounts across six income brackets in our study population. Normalized by group size, the uptake of discounts is roughly uniform across income brackets. However, because EV drivers skew wealthier in our study and in observed adoption trends, high-income households earned the majority of financial discounts for workplace charging. While we paid $\$1,667$ in discounts to the highest income group, the lowest income group received only $\$216$. Given that current EV drivers are wealthier, providing financial incentives to shift these 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.

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, 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.

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, driver's responsiveness to off-peak charging hours hinges on the utilization and reliability of the network. Second, commuters' perceptions of charger availability resulted in overnight charging sessions. 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 5 Â¢$/kWh$ 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'sunique 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.

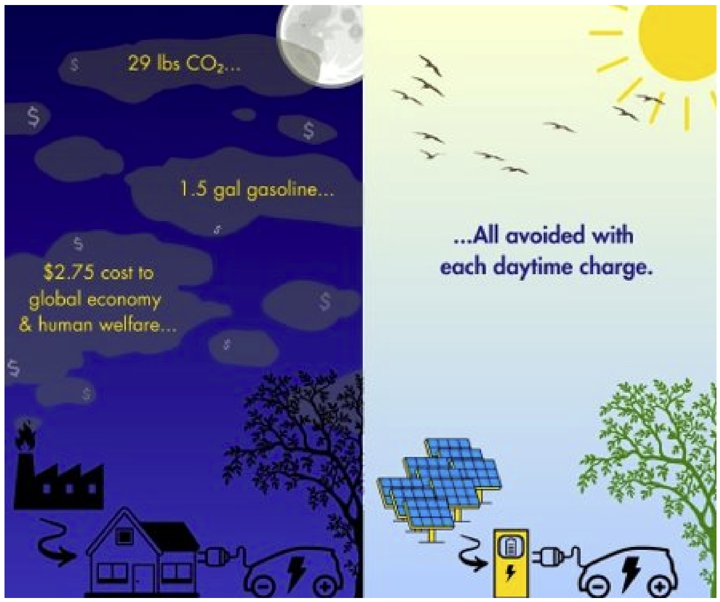


Figure A1: Infographic included with the informational prompt

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

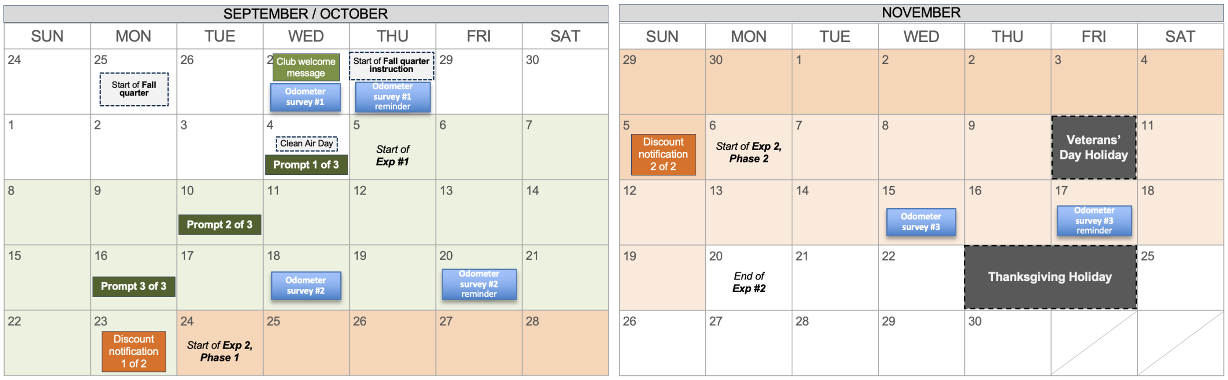
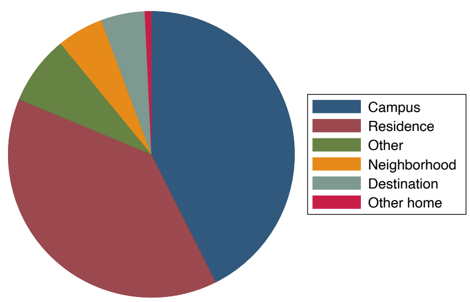


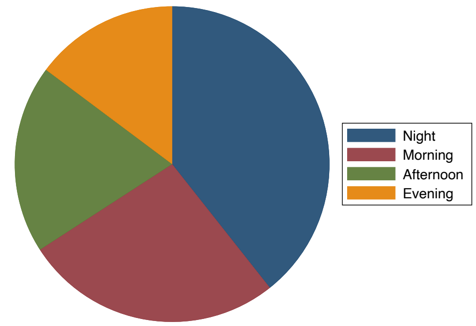
Figure A2: Experimental schedule for the three interventions

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.

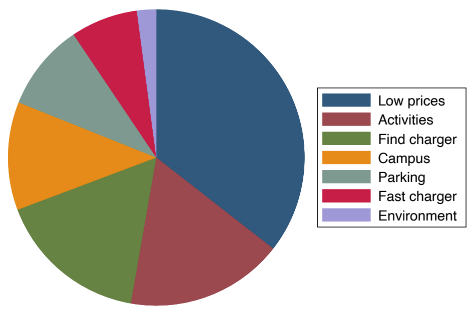
A.5. Triton Charger EV club members



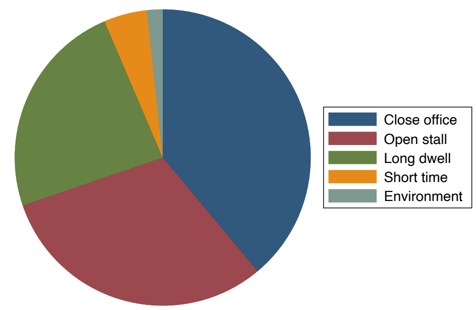
(a) Charging location



(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.

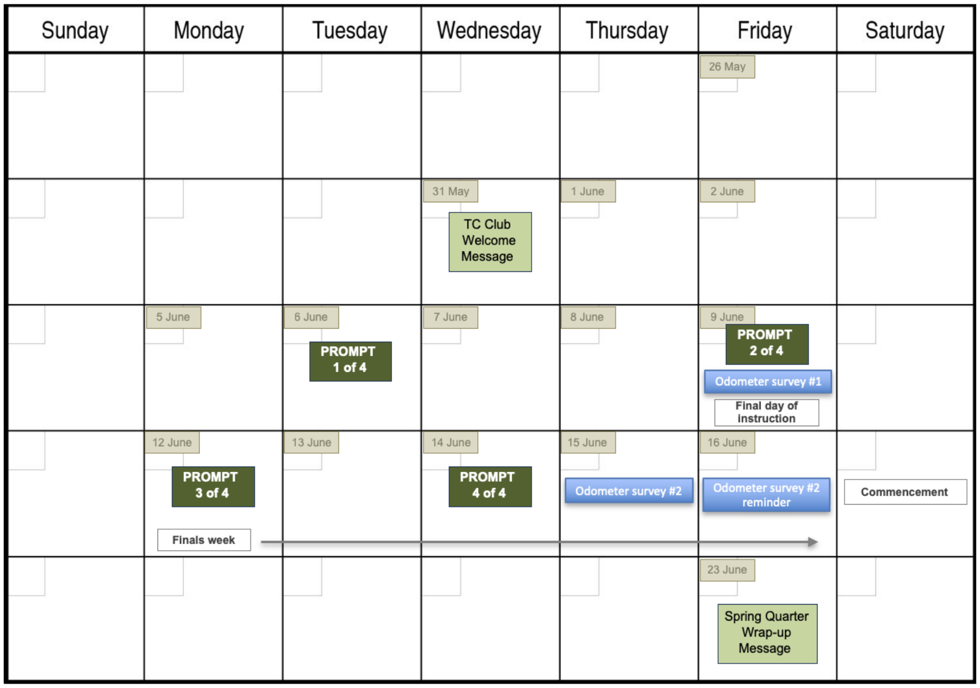


Figure A4: Experimental schedule for the spring trial experiment

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

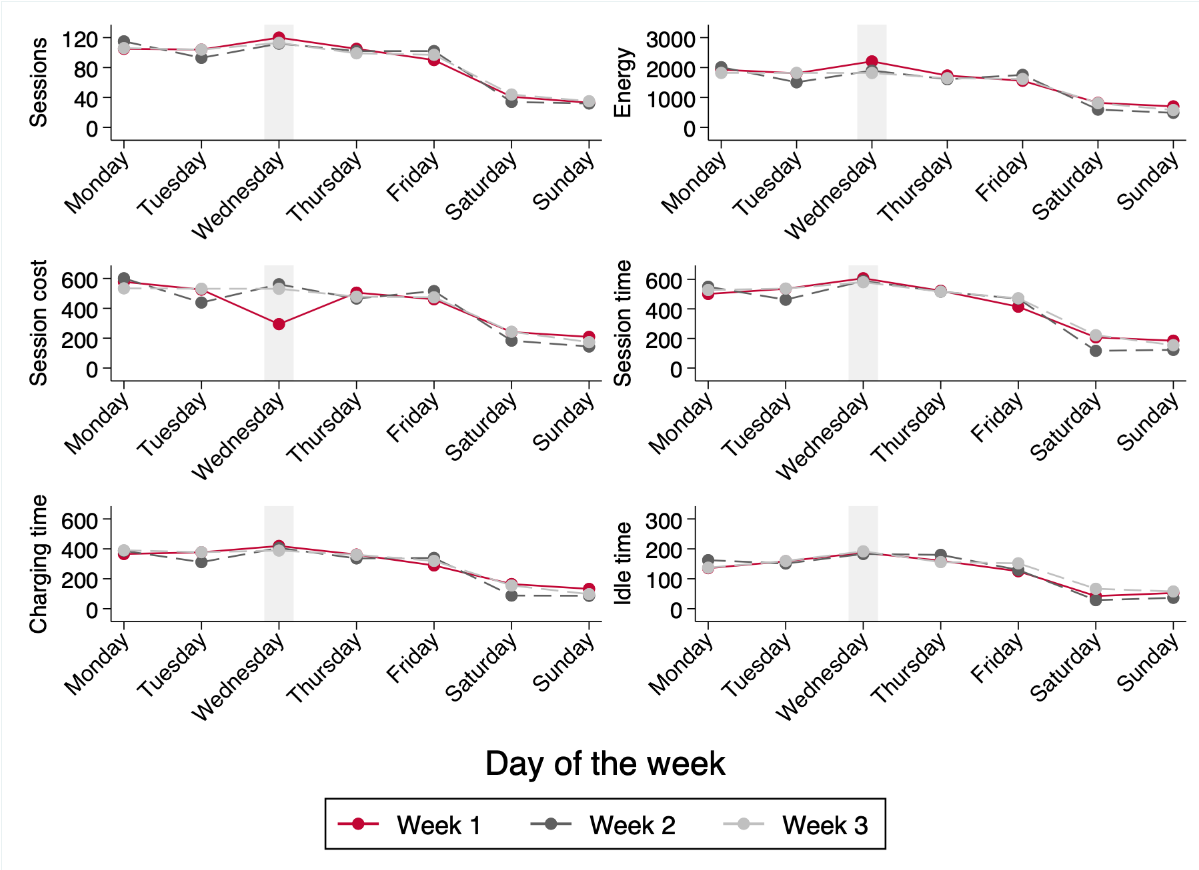


Figure A5: Charging activity around Clean Air Day by day of the week

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.

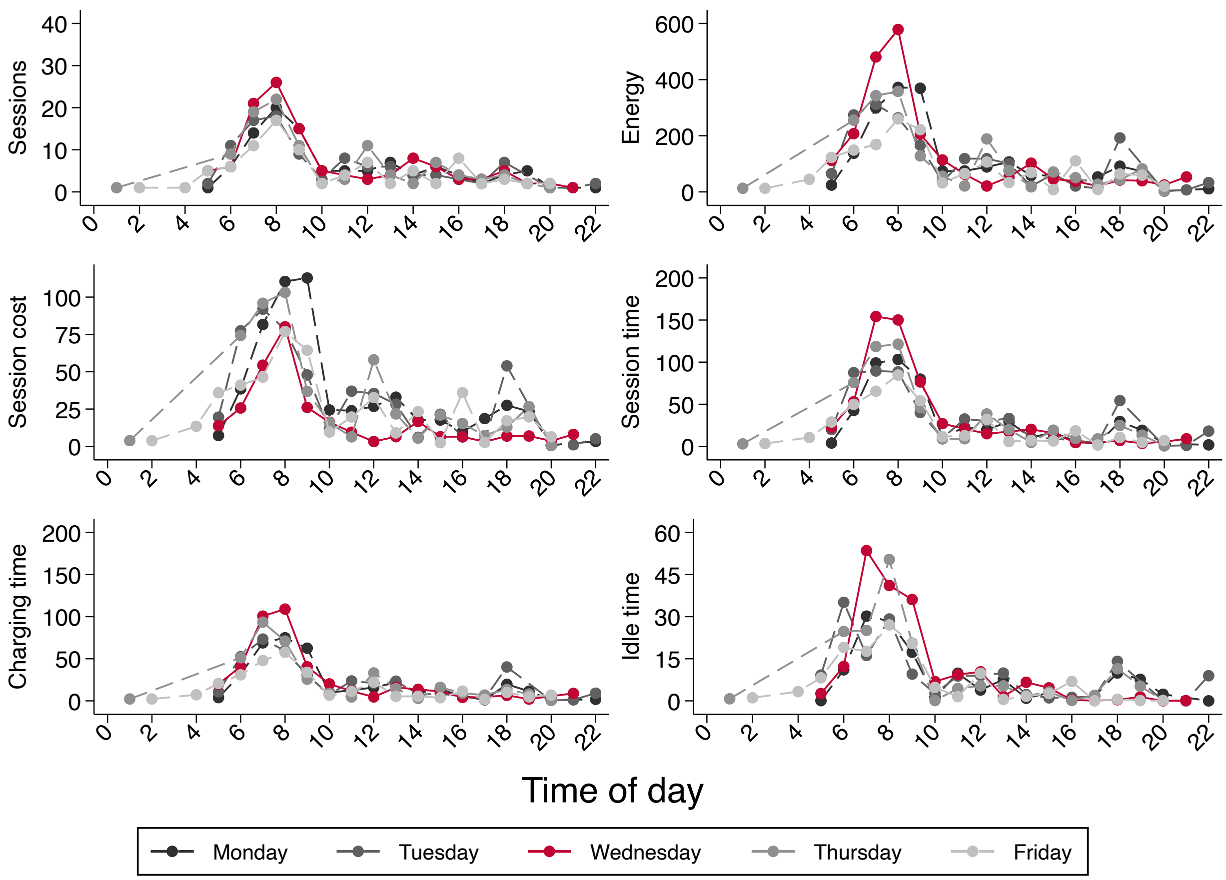


Figure A6: Charging activity around Clean Air Day by time of day

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.

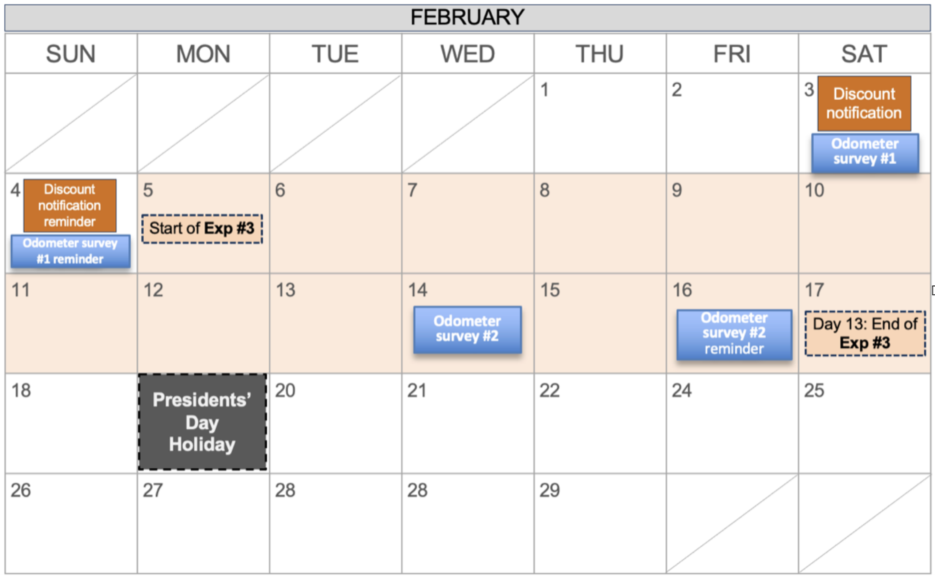


Figure A7: Experimental schedule for the scarcity experiment

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.

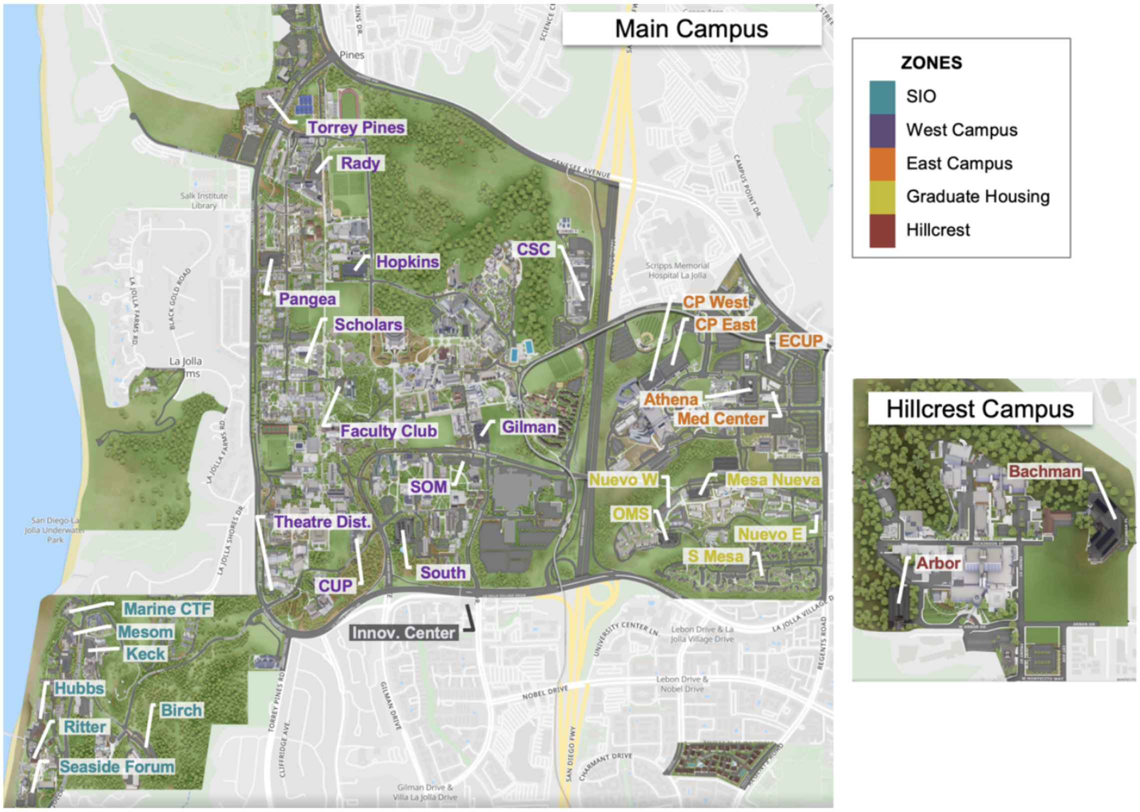


Figure B1: Parking zones and plazas at UCSD

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.

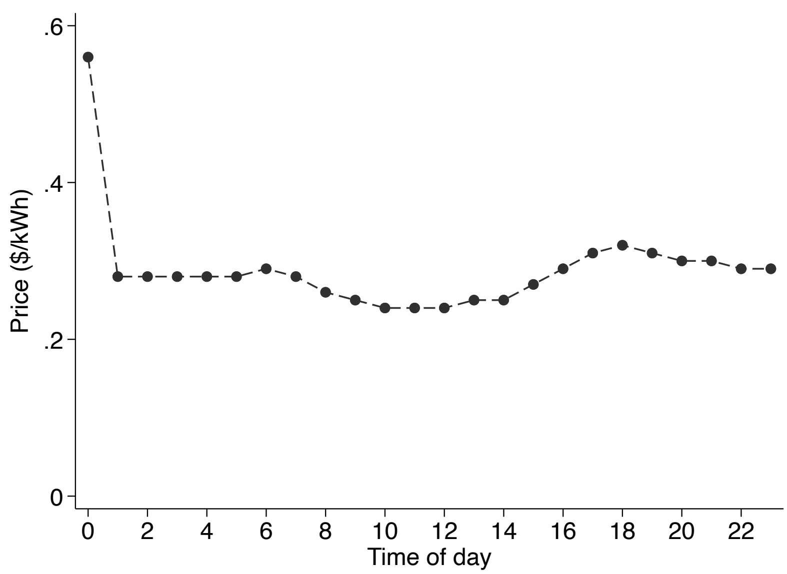


Figure B2: SDG&E public retail EV charging rates

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.

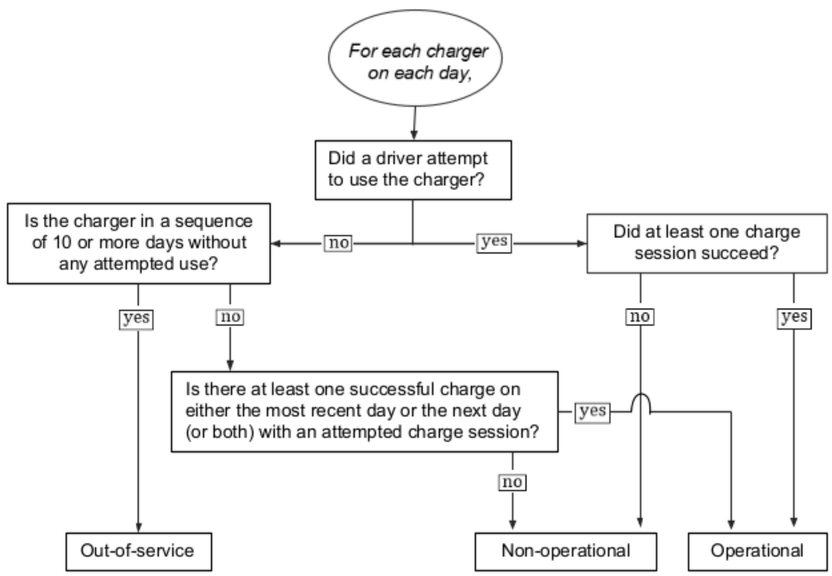


Figure B3: Network operation flowchart

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.

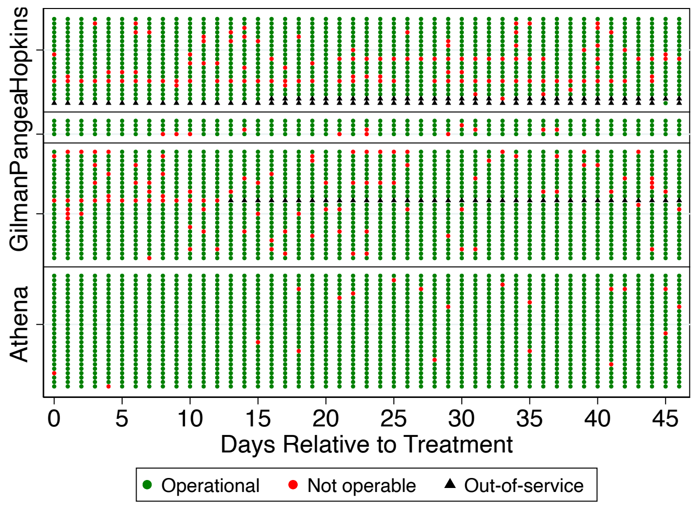


Figure B4: PowerFlex charger designation by day

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.

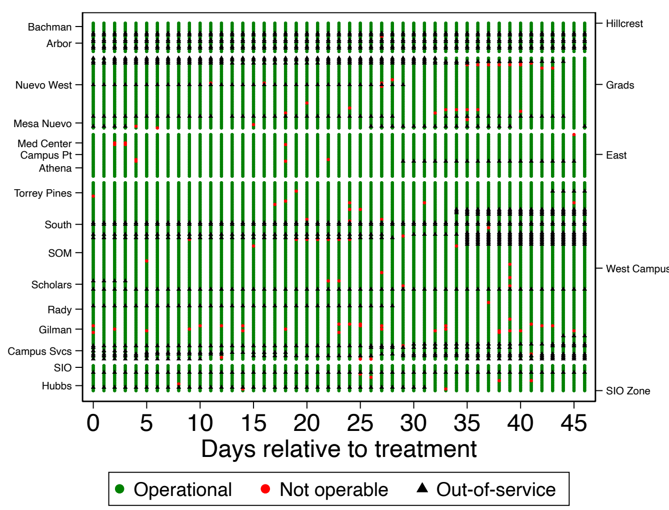


Figure B5: ChargePoint charger designation by day

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.

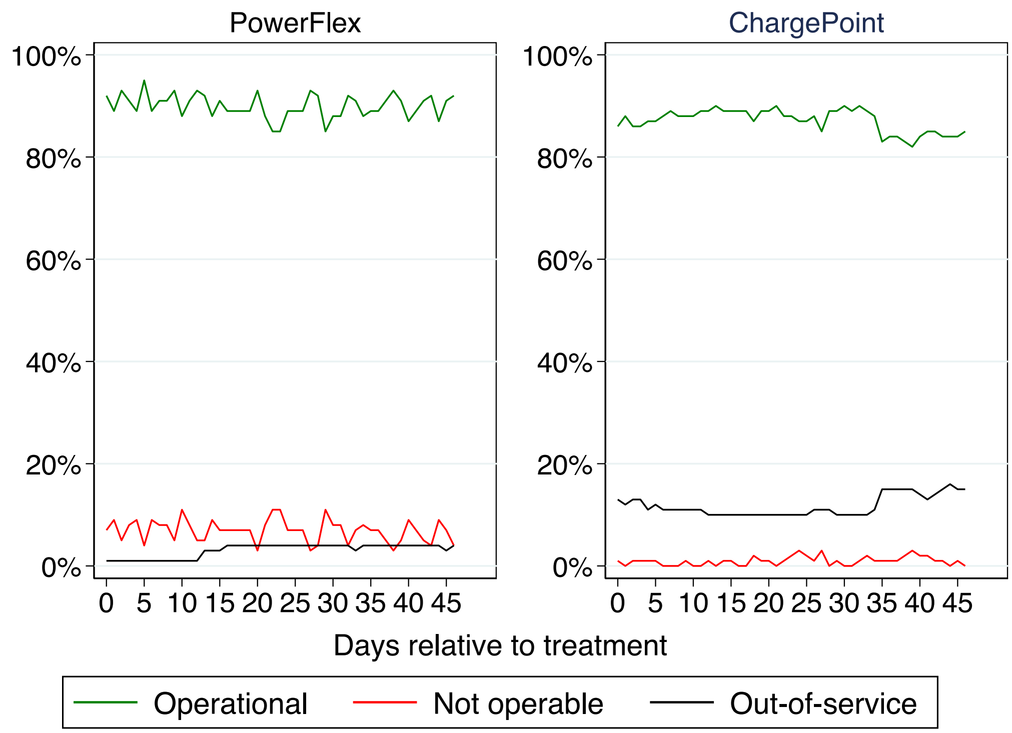


Figure B6: Charge port designation share

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

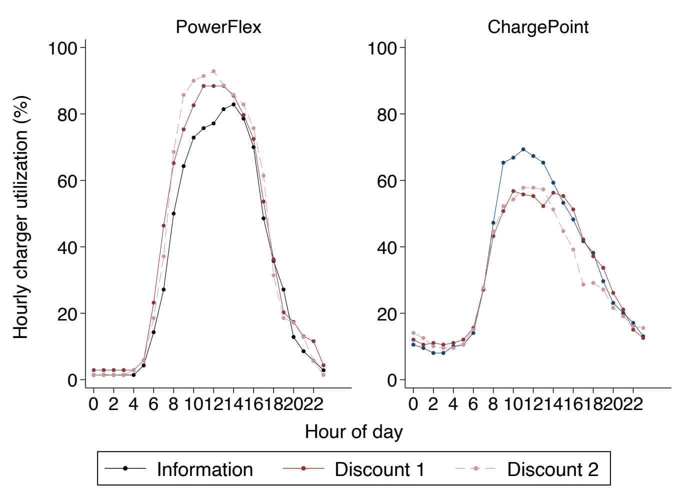


Figure B7: Monday's utilization by time of day and vendor

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).

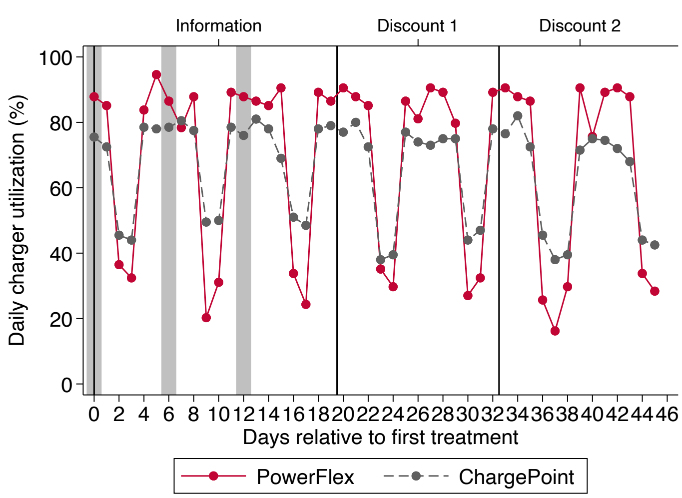


Figure B8: Network utilization by day

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

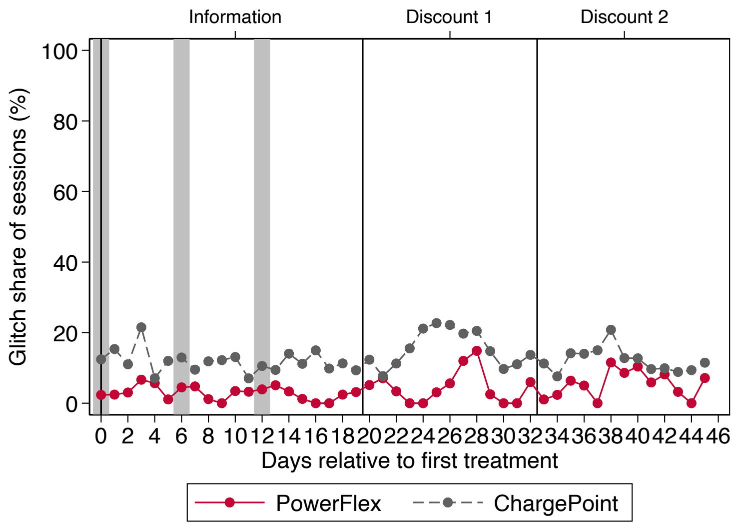


Figure B9: Charging session glitch rate

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.

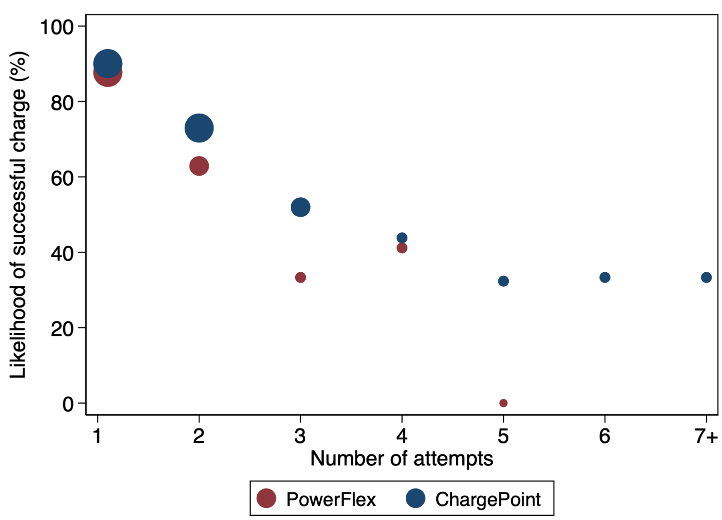


Figure B10: Probability of workplace charging by attempts

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

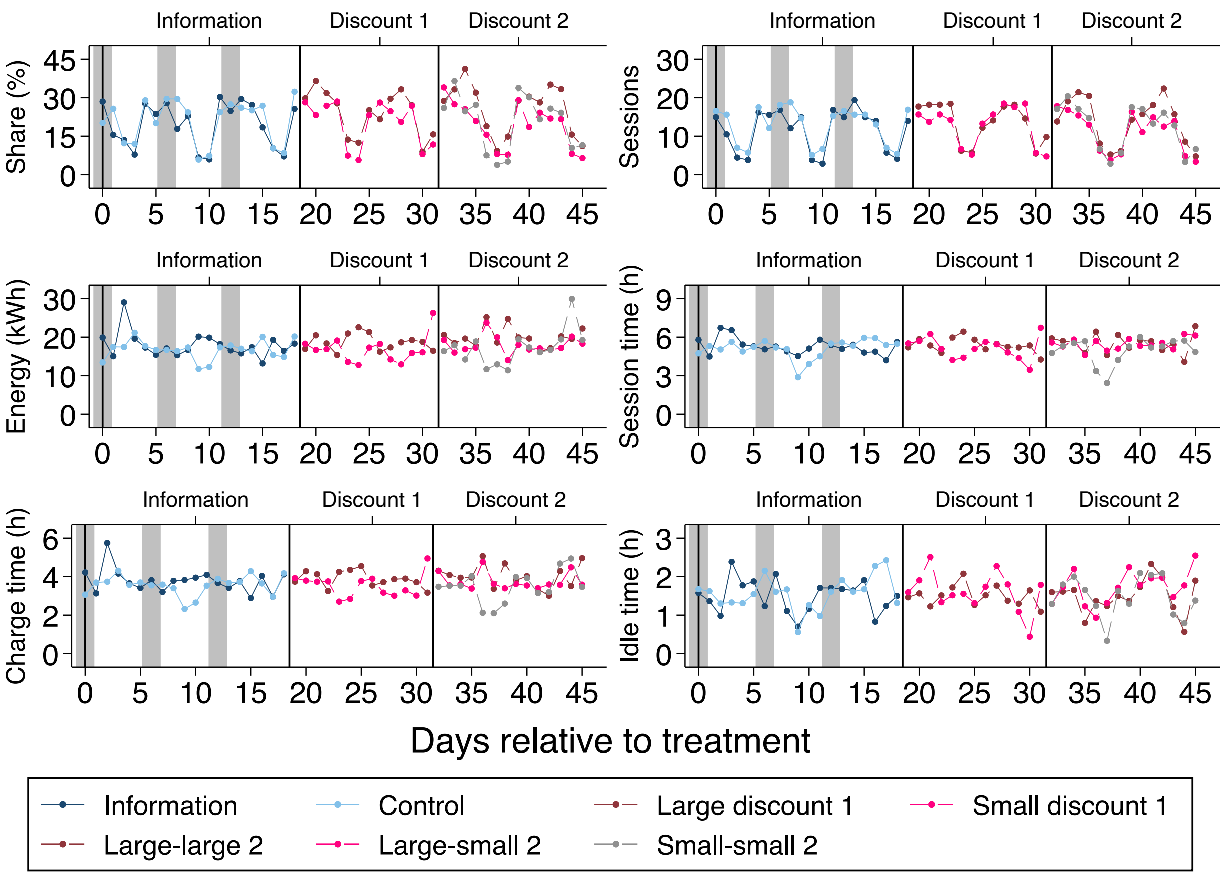
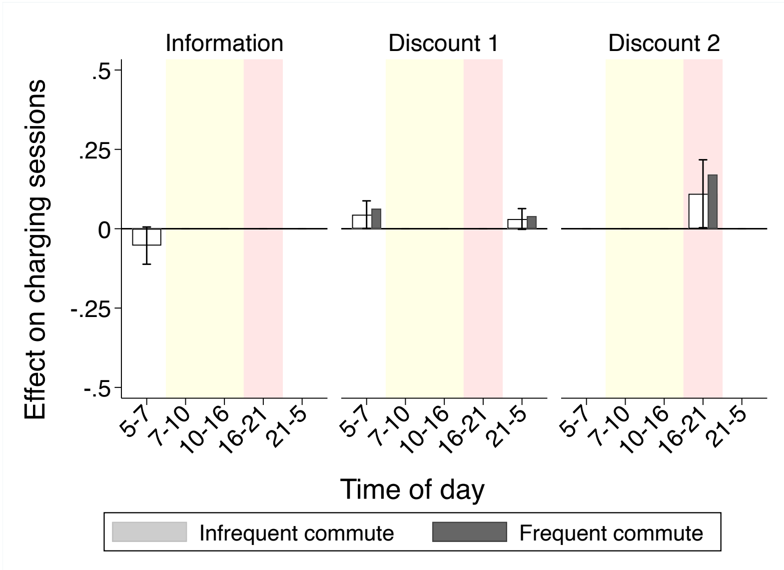
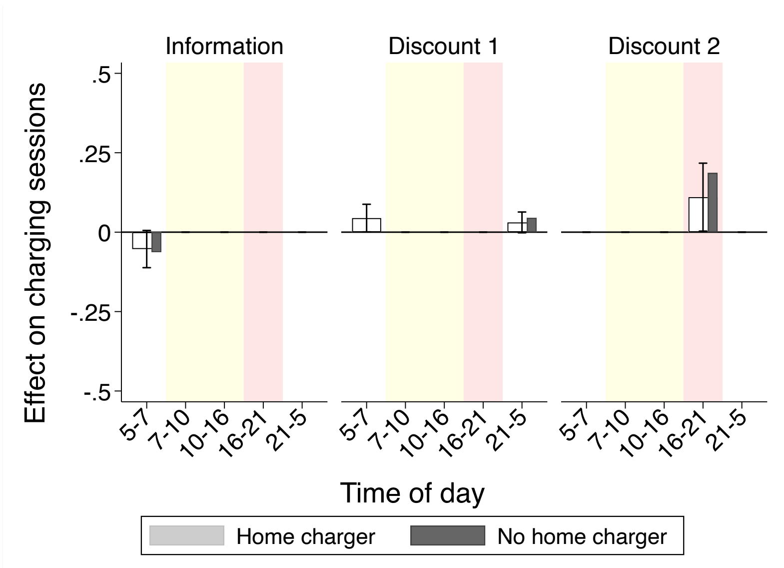


Figure C1: Total charging behavior by day

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.



(a) Commute frequency



(b) Access to home charger

Figure C2: Effect on the timing of charging by driver characteristics

Notes: This figure displays the significant regression estimates (hollow bar) for the time of day in which sessions are initiated across the informational (left), first financial (middle), and second financial treatment (right). We show significant treatment effects (solid bars) on the timing of charging sessions for two mechanisms: Commute frequency (Panel a), and access to home charging (Panel b). Morning and midday periods are associated with low grid carbon intensity (7 - 16; depicted in yellow), whereas evening periods typically exhibit higher carbon intensity (16 - 21; depicted in red). All coefficients are reported in individual×week. We set statistically insignificant estimates to 0. 95%-confidence intervals are indicated through whiskers and reflect robust standard errors.

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	-.046*	.094	-.033	-.022	-.017
	(.027)	(.058)	(.047)	(.035)	(.013)
Weekly plug-ins per driver	.07	.38	.29	.16	.04
B. Discount 1	.046*	.007	-.012	-.027	.045*
	(.025)	(.066)	(.057)	(.044)	(.025)
Weekly plug-ins per driver	.08	.44	.33	.17	.05
C. Discount 2	-.028	-.034	.041	.095*	.000
	(.039)	(.071)	(.061)	(.057)	(.022)
Weekly plug-ins per driver	.09	.38	.27	.16	.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. 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 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	.092	-.037	-.036	-.007
	(.031)	(.067)	(.054)	(.038)	(.010)
Week 2	-.036	.079	-.012	-.020	-.007
	(.031)	(.066)	(.054)	(.040)	(.019)
Week 3	-.050**	.066	-.015	.003	-.008
	(.022)	(.045)	(.040)	(.029)	(.013)
B. Discount 1					
Week 1	.054**	.033	-.033	-.051	.029
	(.022)	(.069)	(.049)	(.051)	(.023)
Week 2	.028	-.032	-.020	-.014	.028**
	(.028)	(.056)	(.056)	(.030)	(.013)
C. Discount 2					
Week 1	-.065	-.089	.074	.124*	.040
	(.045)	(.073)	(.058)	(.068)	(.028)
Week 2	.004	.026	.024	.111**	.007
	(.038)	(.080)	(.072)	(.053)	(.039)

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. 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 C3: 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	-4.501	-.177	-1.263	-83.262*	-19.733	-63.528**
	(8.802)	(.124)	(2.161)	(44.724)	(28.000)	(25.906)
Weekly mean dep. var.	27.1	.91	15.47	302.88	200.9	101.98
Observations	71	419	419	419	419	419

Notes: This table presents the regression estimates of the spring trial informational intervention (Panel A). 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 C4: Effect on additional charging behavior

	Additional charging behavior			
	(1) Vehicle miles	(2) Total energy	(3) Weekend	(4) DC Fast Charger
A. Information	-21.192	-4.336	-.146	.022
	(16.567)	(4.170)	(.518)	(.323)
Weekly mean dep. var.	144.25	37.88	1.82	.7
B. Discount 1	-13.460	-1.870	.794	-.206
	(18.264)	(4.449)	(.649)	(.309)
Weekly mean dep. var.	144.25	37.88	2.37	.41
C. Discount 2	19.081	4.247	1.006	-.187
	(19.299)	(4.985)	(.992)	(.488)
Weekly mean dep. var.	139.46	36.77	2.97	.47

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). 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 C5: Effect on average charging behavior

	Average charging behavior			
	(1) Energy	(2) Session time	(3) Charge time	(4) Idle time
A. Information	-.168	-9.223	-1.958	-7.264
	(.816)	(13.100)	(10.062)	(6.981)
Mean per charge session	9.9	170.48	124.03	46.45
B. Discount 1	1.528*	20.467	18.065*	2.402
	(.870)	(12.779)	(10.371)	(6.240)
Mean per charge session	9.87	162.22	120.94	41.28
C. Discount 2	1.128	26.682	12.464	14.227
	(1.197)	(16.783)	(12.921)	(9.624)
Mean per charge session	10.48	174.88	122.8	52.07
D. Information x large discount	-.912	-23.564**	-14.827	-8.740
	(.754)	(11.785)	(9.110)	(6.972)
Observations	629	629	629	629

Notes: This table presents the regression estimates on the average charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C), as well as interaction effects (Panel D). The outcome variables indicate the average energy consumed, in kWh (column 1); average session duration, in minutes (column 2); average charging duration (column 3); and average idle duration (column 4). 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 C6: 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	-.068*	.093	-.089	.070	.011
	(.041)	(.107)	(.099)	(.108)	(.026)
Low Environmental Motivation	-.043	.087	-.017	-.029	-.010
	(.028)	(.059)	(.045)	(.031)	(.011)
B. Financial incentive 1					
High Environmental Motivation	.051*	.091	.039	-.080	.031
	(.029)	(.148)	(.137)	(.124)	(.038)
Low Environmental Motivation	.044*	-.009	-.035	-.064	.031*
	(.023)	(.062)	(.049)	(.076)	(.018)
C. Financial incentive 2					
High Environmental Motivation	.004	-.023	.044	.049	-.048
	(.073)	(.203)	(.151)	(.088)	(.082)
Low Environmental Motivation	-.050	-.022	.057	.126**	.033
	(.036)	(.069)	(.067)	(.056)	(.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. 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 C7: 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	-.045	-.023	.055	.118**	.025
	(.035)	(.067)	(.064)	(.054)	(.029)
Large-large vs. Small-small	-.042	-.044	.051	.113**	.027
	(.036)	(.068)	(.062)	(.050)	(.030)
Large-small vs. Small-small	-.003	.022	.004	.005	-.001

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). 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 C8: 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	-.024	.248	-14.432	-1.879	-12.536
	(.103)	(1.960)	(35.849)	(26.001)	(16.658)
Week 2	.003	.594	1.945	8.708	-6.761
	(.107)	(2.005)	(36.599)	(25.457)	(17.998)
Week 3	-.003	-1.345	-29.597	-19.955	-9.656
	(.066)	(1.455)	(28.633)	(20.788)	(13.709)
B. Discount 1					
Week 1	.032	3.896*	36.312	45.145*	-8.840
	(.109)	(2.174)	(39.101)	(26.642)	(20.193)
Week 2	-.009	2.056	17.316	21.486	-4.152
	(.092)	(1.784)	(31.847)	(22.319)	(15.619)
C. Discount 2					
Week 1	.085	1.989	25.800	25.489	.337
	(.127)	(2.858)	(44.531)	(32.988)	(17.682)
Week 2	.173	2.315	44.251	25.437	18.817
	(.141)	(2.544)	(48.137)	(33.915)	(23.327)

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). 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 C9: 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	-.053*	.088	-.021	-.018	-.008
	(.030)	(.060)	(.045)	(.031)	(.011)
Weekly plug-ins per driver	.07	.35	.26	.13	.03
B. Discount 1	.040*	-.028	-.034	-.030	.030
	(.023)	(.062)	(.048)	(.037)	(.019)
Weekly plug-ins per driver	.07	.41	.27	.14	.04
C. Discount 2	-.047	-.056	.058	.110**	.020
	(.036)	(.066)	(.067)	(.055)	(.030)
Weekly plug-ins per driver	.09	.36	.31	.14	.05
D. Information x large discount	-.038	.053	-.000	-.014	-.004
	(.025)	(.064)	(.045)	(.035)	(.012)
Observations	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) 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. 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 C10: Effect on the timing of charging with baseline charging controls

	Timing of initiated charging session				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Information	-.044*	.097*	-.018	-.015	-.007
	(.026)	(.051)	(.038)	(.030)	(.011)
B. Discount 1	.037*	-.023	-.014	-.041	.028*
	(.020)	(.058)	(.044)	(.040)	(.017)
C. Discount 2	-.051	-.016	.068	.111**	.026
	(.033)	(.064)	(.064)	(.051)	(.029)

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). 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. All regressions include individual demographic, vehicle, charging infrastructure, and motivational control variables, baseline charging outcomes, 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 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	.010	-.058	.025	.023	.005
	(.011)	(.049)	(.029)	(.019)	(.005)
West Campus	-.137	.539	.068	-.158	-.087
	(.110)	(.332)	(.156)	(.116)	(.070)
East Campus	-.334	.067	-.022	-.021	-.025
	(.275)	(.254)	(.053)	(.184)	(.037)
Graduate Housing	-.070	.132*	-.099	-.034	-.022
	(.090)	(.074)	(.154)	(.037)	(.020)
B. Discount 1					
SIO	-.010	-.098*	-.020	-.010	.000
	(.016)	(.053)	(.018)	(.025)	(.)
West Campus	-.045	.147	.041	-.066	-.008
	(.129)	(.369)	(.157)	(.112)	(.076)
East Campus	.460***	-.077	-.007	-.207	.056*
	(.172)	(.218)	(.069)	(.306)	(.032)
Graduate Housing	.000	.028	-.242	.011	.155
	(.)	(.099)	(.161)	(.043)	(.132)
C. Discount 2					
SIO	.000	-.013	.003	.000	.000
	(.)	(.035)	(.002)	(.)	(.)
West Campus	-.127	-.318	.105	.339*	.096
	(.177)	(.387)	(.231)	(.188)	(.090)
East Campus	.096	-.115	.032	.373	.000
	(.334)	(.240)	(.058)	(.241)	(.)
Graduate Housing	.088	.156	.045	.073	.184
	(.062)	(.128)	(.068)	(.075)	(.234)

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. 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 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	-.048*	-.028	.057	.060*	.021
	(.029)	(.050)	(.041)	(.031)	(.020)
B. Discount	.056	.008	.026	.006	.027*
	(.035)	(.053)	(.043)	(.033)	(.016)
C. Scarcity x large discount	-.000	-.036	.050	.042	.043
	(.030)	(.058)	(.053)	(.036)	(.029)
Weekly plug-ins per driver	.08	.37	.23	.13	.04
Observations	629	629	629	629	629

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. 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.

Table C13: 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	-2.130	.066	.228	2.544	8.161	-5.625
	(2.543)	(.074)	(1.463)	(25.777)	(18.074)	(13.196)
B. Discount	-1.117	.110	2.749*	45.605*	22.803	22.801
	(2.588)	(.072)	(1.559)	(26.390)	(18.297)	(15.256)
C. Scarcity x large discount	-3.648	.092	2.231	23.163	24.844	-1.693
	(2.793)	(.089)	(1.754)	(30.005)	(20.783)	(14.804)
Weekly mean dep. var.	30.32	.84	15.33	273.13	195.65	77.49
Observations	351	629	629	629	629	629

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). 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 C14: 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	-2.323	.020	-.899	-40.253	-10.857	-29.399*
	(5.077)	(.103)	(2.105)	(36.180)	(26.409)	(15.525)
Frequent Commute	5.452	-.023	.158	-3.589	-1.937	-1.648
	(3.864)	(.108)	(1.964)	(38.316)	(26.513)	(19.419)
B.Discount 1						
Infrequent Commute	1.736	-.006	.678	-16.547	-1.310	-15.238
	(5.065)	(.121)	(2.480)	(40.202)	(29.747)	(17.340)
Frequent Commute	-1.712	.022	4.511*	52.332	55.081*	-2.740
	(4.429)	(.115)	(2.334)	(43.306)	(30.449)	(22.287)
C.Discount 2						
Infrequent Commute	-12.182**	-.099	-2.964	-23.436	-41.246	17.828
	(5.669)	(.168)	(2.814)	(45.673)	(34.795)	(20.482)
Frequent Commute	3.271	.240	4.484	62.820	58.271	4.563
	(5.549)	(.151)	(3.375)	(61.294)	(42.857)	(27.583)

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). 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 C15: 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	-.023	-.001	.084	-.068	-.004
	(.031)	(.061)	(.071)	(.041)	(.012)
Medium Charge Rate	-.027	.110	-.034	-.032	-.015
	(.032)	(.071)	(.054)	(.039)	(.012)
High Charge Rate	-.116***	.113	-.102	.061	.008
	(.042)	(.105)	(.078)	(.064)	(.030)
B. Discount 1					
Low Charge Rate	.036	-.090	-.043	-.046	.002
	(.036)	(.102)	(.064)	(.049)	(.018)
Medium Charge Rate	.046*	.004	-.019	-.036	.021
	(.027)	(.067)	(.059)	(.045)	(.022)
High Charge Rate	.049	.099	-.040	-.018	.095**
	(.064)	(.124)	(.087)	(.076)	(.041)
C. Discount 2					
Low Charge Rate	-.007	-.104	.046	.097*	-.011
	(.045)	(.104)	(.082)	(.053)	(.041)
Medium Charge Rate	-.070**	-.052	.102	.102	.047
	(.035)	(.076)	(.083)	(.072)	(.047)
High Charge Rate	-.005	.146	-.072	.188*	-.005
	(.102)	(.166)	(.093)	(.108)	(.039)

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. 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 the timing of charging by vehicle type

	Outcome Variable				
	(1) 5-7	(2) 7-10	(3) 10-16	(4) 16-21	(5) 21-5
A. Informational prompt					
Battery Electric	-.055*	.078	-.036	-.011	-.004
	(.031)	(.059)	(.048)	(.030)	(.011)
Plug-in Hybrid	-.013	.117	.013	-.047	-.019
	(.049)	(.133)	(.103)	(.093)	(.031)
B. Financial incentive 1					
Battery Electric	.049**	-.025	-.033	-.036	.039**
	(.024)	(.065)	(.053)	(.040)	(.020)
Plug-in Hybrid	.028	.095	-.011	-.031	-.001
	(.057)	(.151)	(.127)	(.112)	(.028)
C. Financial incentive 2					
Battery Electric	-.043	-.012	.054	.142***	.040
	(.041)	(.077)	(.064)	(.047)	(.030)
Plug-in Hybrid	-.050	-.053	.060	.046	-.019
	(.061)	(.170)	(.160)	(.159)	(.067)

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. 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 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	3.512	-.011	1.629	-1.097	3.700	-4.788
	(5.054)	(.112)	(2.616)	(39.304)	(29.760)	(16.931)
Medium Charge Rate	3.510	.002	-.315	-16.958	-2.126	-14.835
	(3.641)	(.106)	(1.951)	(37.539)	(27.251)	(18.761)
High Charge Rate	.729	-.036	-1.606	-25.667	-20.411	-5.250
	(7.680)	(.159)	(3.016)	(56.096)	(38.037)	(26.259)
B. Discount 1						
Low Charge Rate	-3.783	-.140	-.902	-24.343	-14.484	-9.847
	(5.047)	(.145)	(2.399)	(46.784)	(31.328)	(24.442)
Medium Charge Rate	-.694	.016	3.138	38.491	42.137	-3.638
	(4.105)	(.106)	(2.101)	(39.540)	(27.504)	(20.406)
High Charge Rate	4.602	.185	8.381**	61.970	76.394	-14.432
	(7.167)	(.194)	(4.042)	(69.985)	(47.987)	(31.774)
C. Discount 2						
Low Charge Rate	-4.521	.023	-2.060	-18.414	-27.314	8.907
	(6.184)	(.156)	(3.264)	(57.041)	(38.487)	(29.733)
Medium Charge Rate	-1.162	.110	1.052	26.446	22.937	3.529
	(5.504)	(.151)	(3.232)	(52.075)	(41.041)	(21.840)
High Charge Rate	-.267	.259	8.433	104.066	78.153	25.924
	(8.287)	(.224)	(5.902)	(100.634)	(68.115)	(41.546)

Notes: This table presents the regression estimates on total charging behavior of the informational (Panel A), first financial (Panel B), and second financial treatment (Panel C) by the typical rate that participants pay for EV charging. Low rates are those <\$.17/kWh; medium rates, ≥\$.17/kWh and <\$.23/kWh; and high rates, ≥\$.23/kWh. The outcome variables indicate the share of 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). 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.

D. Details of calculating the effect from charging

In this Section, we provide additional details to derive the annual social CO_2 emission damages, the marginal cost of supplying electricity, and LCFS revenues from EV charging.

Expressing the societal and institutional effect of the shifts in charging behavior in percentage terms requires us to estimate the social costs of CO_2 emission damages, electricity cost of charging, and LCFS revenues from EV charging per driver. Below, we describe how we use our charging network and driver data to back out these three empirical objects. To estimate the annual effects per driver, we convert the average energy consumed over the experiment (19 days of informational prompts, 13 days of the first discount, and 14 days of the second discount) to annual energy consumption.

D.1. Deriving emissions, cost of charging, and LCFS revenues

We estimate the 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:

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

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:

$$CO_2^{location} \;=\; \frac{\sum_{h=1}^{24} E_h}{Share_E^{work}} \cdot (1 - Share_E^{work}) \;\cdot\; \overline{CI} \cdot\; SCC. \tag{2}$$

The social workplace and home charging CO_2 emission damages from charging are equal to \$148.66 (.71t CO_2) per driver annually.

We estimate the marginal cost of supplying electricity for EV charging as the product of annual hourly energy consumed at work E_h, and the average LMP of electricity at UCSD's pricing nodes LMP_h as follows:

$$LMP^{timing} \;=\; \sum_{h=1}^{24} E_h \;\cdot\; LMP_h. \tag{3}$$

Similar to the CO_2 emissions from charging, we use the driver's share of energy charged at work to derive the energy consumption from home charging. We then compute the annual marginal cost of supplying electricity for EV charging from home charging as the annual energy consumption of home charging and the LMP of electricity from the pricing nodes at Triton Club members' home address $\overline{LMP^{home}}$ as follows:

$$LMP^{location} = \frac{\sum_{h=1}^{24} E_h}{Share_E^{work}} \cdot (1 - Share_E^{work}) \cdot \overline{LMP^{home}} \tag{4}$$

The LMP of electricity from charging at UCSD and the most typical home pricing nodes correspond to \$147.58 per driver annually.

We estimate the annual revenues earned through California's LCFS program from workplace charging as the product in electricity consumption at work $E_h$and the carbon intensity of electricity CI_h at that hour as follows:

$$LCFS^{timing} = \sum_{h=1}^{24} (CI_{standard} - \frac{CI_h}{3.4}) \cdot E_h \cdot \bar{P} \cdot 3.4. \tag{5}$$

Inserting the carbon intensity from gasoline-powered cars $CI_{standard}$ and the LCFS credit price $\bar{P}$, we estimate annual LCFS revenues of \$44.67 per driver from workplace EV charging.

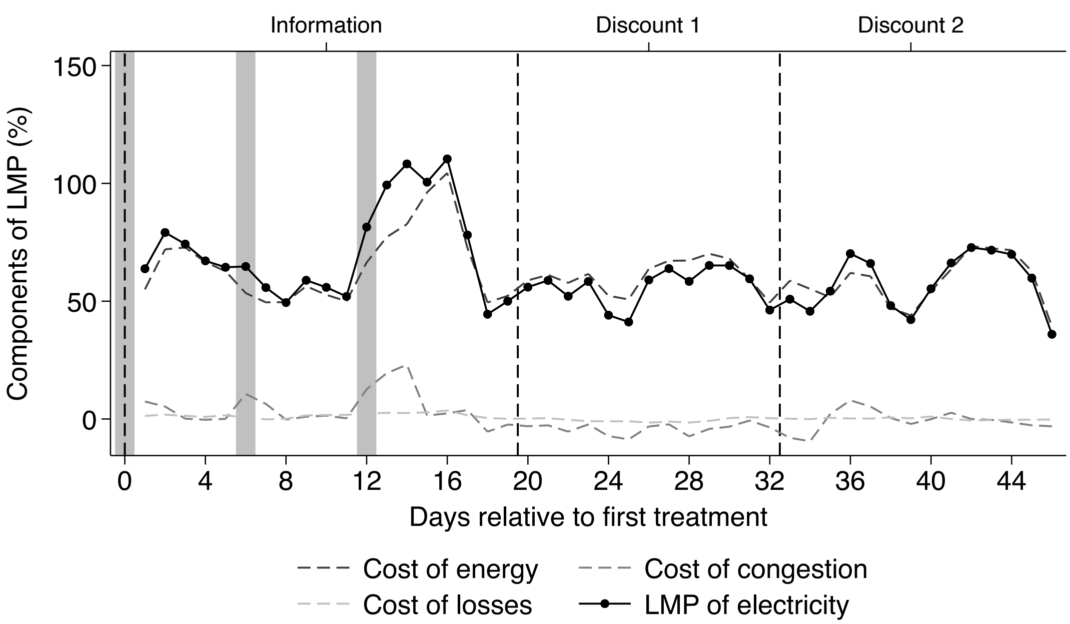


Figure D1: LMP components in electricity

Notes: This figure illustrates daily variations in electricity LMP at UCSD's pricing nodes alongside its three components: energy cost, congestion cost, and losses cost by day in the experiment. Day 0 denotes the first day of the informational treatment. Vertical lines denote the start of each intervention; thick gray lines denote days on which the informational prompt was sent.