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## Can Electric Vehicles Aid the Renewable Transition? Evidence from a Field Experiment Incentivising Midday Charging

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# Can Electric Vehicles Aid the Renewable Transition? Evidence from a Field Experiment Incentivising Midday Charging

## Abstract

In a field experiment tracking 390 electric vehicles minute-by-minute, we show that incentives reduce charging by 17%—27% during peak times and increase it by 34% during midday when solar generation is highest. Peak charging decreases at home, while midday charging rises out of the home. Participants shift and reduce charging, drive less, and run batteries lower. We find heterogeneity based on rooftop solar ownership, commuting, and having a fast home charger. These findings suggest electric vehicles can support the shift from fossil fuels to renewable energy and highlight the enabling role of charging infrastructure.

JEL-Codes: Q410, Q420, Q480, R410.

Keywords: electric vehicles, field experiment, renewable energy, rooftop solar, dynamic electricity prices.

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# 1 Introduction

The transition to a decarbonized energy system is one of the defining challenges of the 21<sup>st</sup> century. To avoid catastrophic climate change, global greenhouse gas emissions must reach net zero by 2050 (Masson-Delmotte et al., 2019). The path to net-zero emissions starts with decarbonizing electricity generation and electrifying energy end-uses like transportation and heating. However, the rise of variable renewable energy sources such as wind and solar photovoltaics and new electric loads like electric vehicles (EVs) present a challenge for power systems. Wind and solar output vary over minutes, hours, and days, while new loads such as EVs could substantially increase peak electricity demand (Bunsen et al., 2018). These changes will require power systems to become more flexible, for example, by shifting electricity demand to match the availability of renewable energy and increasing energy storage.

EVs could provide a key source of flexibility by acting as “batteries on wheels”—charging when renewable output is high and discharging back when renewable output is low. However, the extent to which EVs can play this role depends crucially on when they are charged and the willingness of EV owners to sell energy in spare battery capacity to the grid. The charging decisions of individual EV owners responding to price incentives will ultimately shape the system-level flexibility EVs can provide. Understanding whether and how much EV owners will alter their charging in response to price incentives is therefore key to integrating EVs into high-penetration renewable power systems (Szinai et al., 2020).

In this paper, we present novel evidence on how EV owners respond to price incentives to shift their charging to times that support an electricity network with a high penetration of solar generation. Our study utilizes high-resolution, minute-by-minute telematics data tracking all driving, charging, and vehicle locations to provide a granular and comprehensive view of EV owners’ behavior. This rich dataset allows us to examine the time and location of charging, driving, and battery management.

For a sample of 390 Australian Tesla owners recruited for the study, we first compare the time and location of charging for those with and without rooftop solar. In our setting, rooftop solar owners face strong financial incentives to charge at home when their panels produce power. We find substantial differences in charging behavior. For rooftop solar owners the share of charge during the middle of the day is 76% higher, the share during peak demand times is 33% lower, and the share of charge occurring at home is 14% higher.

We then randomly assign half the sample of vehicle owners to receive incentives to avoid charging during peak demand hours when the grid is most often stressed. Further,

we randomly assign half of non-solar participants to receive an additional incentive to charge their vehicles during hours with high solar generation in the middle of the day. Both incentives are in the order of 50–80% of the average electricity tariff.

We find that incentives substantially shift charging. Payments to reduce peak period charging lead to a 27% reduction by non-solar owners and a 17% reduction by solar owners. Non-solar owners (36% of the sample) who receive both incentives increase midday charging by 34%. We find peak responses are invariant to vehicle owner characteristics, such as whether they commute, have installed a fast home charger or use automated scheduling. Further, peak reductions are predominantly reductions in charging at home. By contrast, increases in midday charging occur mostly out of the home, among commuters, or at home among owners with fast home chargers. These results suggest an important role for public, workplace, and fast home charging infrastructure alongside incentives.

Overall, our results demonstrate price incentives significantly reshape EV charging loads. Incentives in the range of current electricity prices (AUD 0.25–0.40 per kWh in our setting) can motivate EV owners to charge in a manner compatible with high renewable energy shares. Price signals can shift EV loads to support, rather than strain, renewable electricity grids.

We also find solar owners respond to incentives differently than non-solar owners. The subsidy for non-solar owners to increase midday charging significantly increases their propensity to charge when solar generation is high. Yet even with this subsidy, non-solar owners still exhibit less midday charging than solar owners who face similar preexisting incentives for self-consumption of their rooftop solar production. The smaller response of solar owners to peak period incentives may be due to a different margin of adjustment: solar owners who are paid to reduce peak charging do so by driving slightly less, with effects more pronounced on weekends and among non-commuters. Non-solar owners instead substitute between charging times.

Despite different margins of adjustment, we find both solar and non-solar vehicle owners receiving incentives allow batteries to discharge to lower levels before recharging. That is, they will wait longer to recharge their batteries to access cheap charging. The willingness of owners to give up battery capacity in return for compensation is critical for EVs to be used as storage once vehicle-to-grid and related technologies become more readily available. Together, our results reinforce that EVs can provide multiple sources of power system flexibility.

Our findings have important implications for policies encouraging the widespread adoption of EVs and policies aiming to manage the impacts of adoption on electricity networks. Worldwide, EV sales surpassed 10 million units in 2022, comprising 14% of

new car sales, and were estimated to reach 14 million units in 2023 (IEA, 2023a). Many jurisdictions offer incentives for EV adoption to reduce road transport emissions (Holland, Mansur and Yates, 2021). However, the extent of emissions reduction by EVs partly depends on the intensity of the marginal electricity generator’s emissions when charging occurs. Our study demonstrates that price incentives can effectively shift EV charging to align with renewable generation, increasing their emissions-reduction benefits while reducing the infrastructure needed to decarbonize the electricity grid. These incentives would likely entail far lower costs than direct public investments in storage or generation. More broadly, by demonstrating how distributed flexibility can be mobilized via price signals, our study underscores the importance of electricity tariff reform as power systems decarbonize.

We study EV charging in a unique and important setting. Australia has the highest per capita production of solar energy (990 W) and rooftop solar installation in the world (IEA, 2022).<sup>1</sup> At current levels, grid-scale solar generation in Australia is already being significantly curtailed, rooftop solar has caused negative operational demand, and the combined impacts of both rooftop and grid-scale solar regularly force wholesale electricity prices in the middle of the day below zero.<sup>2</sup> In many parts of Australia there are also limits on the size of rooftop solar installations designed to ensure the security of local distribution networks. Yet the renewable energy transition has only just begun. In Australia over the next 25 years, grid-scale renewable energy is expected to increase by 700%, storage capacity by 2000%, and consumer-owned distributed energy resources such as rooftop solar, batteries, and EVs by 400% (AEMO, 2024a). At the same time, household and business electricity consumption, which typically peaks in the late afternoon and early evening as solar generation declines, is expected to double. Lessons drawn from this context inform the transformation occurring around the world. Globally, additions to renewable energy capacity were projected to hit a record-breaking 107 gigawatts (GW) in 2023, surpassing the combined installed power capacity of Germany and Spain (IEA, 2023b). Further, Energy Ministers of major economies expect as their energy systems decarbonize, distributed energy resources like rooftop solar and batteries will play a key role (G20, 2021).

Our study of EV charging builds on several bodies of literature. First, a forecasting literature examines the potential of EVs to provide flexibility to the power system as the penetration of variable renewable generation increases (Kester et al., 2018; Richardson,

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<sup>1</sup>36% of dwellings in Australia have rooftop solar (APVI, 2024).

<sup>2</sup>For example, in quarter 4 of 2023, 20% of intervals recorded negative or zero wholesale prices (AEMO, 2024b). Wholesale prices can be negative as baseload generators will pay to maintain their generation and avoid the costs of shutdown and ramp up while renewable generators receive alternative sources of revenue (such as Renewable Energy Certificates) from producing.

2013). We provide empirical evidence to ground these predictions. Second, lab- and survey-based studies investigate how EV owners say they would respond to charging incentives (Parsons et al., 2014; Wolbertus et al., 2018). The revealed preference approach of our field experiment provides clear evidence of how current EV owners do respond. Finally, a small set of field experimental studies examine EV charging. Burkhardt, Gillingham and Kopalle (2023) examine the impact of off-peak (overnight) electricity pricing on electricity use and EV charging at home.<sup>3</sup> The closest study to ours is Bailey et al. (2023), which provides incentives for off-peak (overnight) EV charging in Canada. They find financial incentives significantly increase the share of charging during the off-peak period, while nudges (using moral suasion) do not. We add to their work by examining a more complex set of incentives, leveraging a new source of telematics data, and exploring heterogeneity based on location of charge and owner characteristics. These additions allow us to paint a rich picture of EV charging flexibility and its potential grid impacts in a high-penetration renewable grid. In particular, our paper is the first to test whether EV owners will shift charging towards the middle of the day when solar generation peaks. We further explore the extent of shifts that occur at home versus out-of-home. Shifting charging from peak to overnight when vehicles are parked and not in use is arguably less challenging than shifting charging towards the middle of the day when vehicles may be in use, not at home, and/or are not near a charging point. Despite this, we find substantial flexibility to shift charging towards midday even with current technology, suggesting EVs could play a key role in managing grids with high renewable penetration.

The remainder of this paper is structured as follows. In Section 2 we describe the data, experimental design and empirical strategy, Section 3 then presents the results, before Section 4 concludes.

## 2 Data, Experimental Design, and Empirical Strategy

We recruited 390 Australian Tesla owners to participate in a study on EV driving and charging. Participants were offered a year of premium Teslascope membership (worth USD 30) and agreed to share minute-by-minute telematics data tracking vehicle driving and charging. Telematics combines telecommunications and informatics to enable remote monitoring and collection of vehicle data. Teslascope is a data recording platform developed for Tesla vehicles collecting telematics data directly from vehicles.<sup>4</sup> To register,

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<sup>3</sup>Interventions testing the effect of time-varying pricing among residential electricity consumers are common. Harding and Sexton (2017) survey these time-varying pricing studies and conclude while peak pricing can significantly reduce peak electricity consumption, the effects are typically small in magnitude without enabling technologies. In Australia, Leroux, Leslie and Ward (2023) test whether incentives will shift non-EV use towards the middle of the day.

<sup>4</sup>Tesla represents the majority of the EV market in Australia (Electric Vehicle Council, 2024).



participants completed a survey of owner characteristics such as owning rooftop solar or home batteries.<sup>5</sup> At the end of the experiment, all participants were asked to answer a follow-up survey and offered an additional year of Teslascope membership and a gift card worth AUD 15–25 depending on their responses. Of the 390 participants, 323 answered the follow-up survey with the probability of answering balanced across Treatment and Control (the p-value for the null hypothesis of balance is 0.69).

We observe charging and driving data in “event” format. A geotagged charging event represents each time a vehicle is plugged in. The charging event includes power delivery over this period, logged every minute. A geotagged driving event represents each time a vehicle starts moving after being shifted from Park gear into Drive and ends when the vehicle is turned off after being shifted back into Park gear. Each driving event contains progress logs at per-minute resolution. For the charging data, we transform the events into an hourly panel assuming the charge in kWh is constant.<sup>6</sup> For our main analysis we exclude negative kWh events (data anomalies commonly due to broken charging stations). For analysis of charging commencement, we exclude events less than 1 kWh, as these may be trickle charges<sup>7</sup> or broken charging stations.

Of the 390 eligible vehicle owners, half were randomly assigned to receive incentives to shift charging. Incentives were offered over three months from Monday 11 September to Friday 8 December 2023. To improve statistical power, treatment assignment was stratified within: recruitment wave (recruited before February 1, after February 1 and before April 6, or after April 6 2023), whether baseline daily charge exceeded 10 kWh, and rooftop solar ownership.

Two participants opted out of receiving incentives while allowing us to collect their data. A further 13 vehicles stopped reporting data before during the experiment (this could occur if vehicles were accidentally logged out or sold, or if participants withdrew). Attrition was balanced across Treatment and Control.<sup>8</sup> We therefore estimate intent to treat effects without accounting for imperfect compliance or attrition as they are both minor. Table 1 reports descriptive statistics and balance on characteristics for Treatment and Control groups and solar (250 owners) and non-solar (140 owners). We find balance

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<sup>5</sup>Our main recruitment commenced in 2023 however 146 participants were recruited for an earlier project. For these participants, we observe driving and charging data from October 2018. We recruited participants through paid advertisements and unpaid coverage in social and traditional media. To remove outliers, participants with more than two Tesla vehicles or an average daily kWh charge > 40 kWh were ineligible. We also excluded members of a voluntary “customer reference group” who advised on the trial. Participants who registered but were ineligible received a year of premium Teslascope membership.

<sup>6</sup>A kWh represents the unit of electric energy consumed, analogous to a liter of water. An EV charging at 5 kW for 1 hour would consume 5 kWh. We aggregate events within an hour.

<sup>7</sup>Low-power charging used to maintain the battery’s charge level.

<sup>8</sup>The p-value for the null that the probability of attrition is the same across Treatment and Control is 0.78.

on observable characteristics at the 95% level and on all but one characteristic for solar owners at the 90% level. When we adjust for multiple hypothesis testing using sharpened q-values that control the false discovery rate, we fail to reject balance for all characteristics (Anderson, 2008).<sup>9</sup>

Table 1 shows the average daily charge of vehicles before the reward period was around 10 kWh per day for solar and non-solar owners and both types of vehicle owners drive approximately 30km per day. The average use of vehicles therefore does not differ across these groups. However, when and where they charge their vehicles differs substantially. In the baseline period, solar owners charged 12–13% during peak times and 43–44% during sun soak times, with 65–68% of charging at home. For non-solar owners, the equivalent shares are 17–20%, 22–27% and 58–59%. Solar owners charge substantially more during the middle of the day, less during peak times, and more at home (p-values for the differences are 0.00, 0.00, and 0.05).

Overall, our sample has the expected profile of EV owners in Australia—the majority are owner-occupiers and approximately 60% have annual income over AUD 130,000.<sup>10</sup> From our follow-up survey, administered after the experiment, we observe that 63% have a fast home charger<sup>11</sup>, approximately 75% use automated scheduling to charge, and 80% commute to work at least once a week.<sup>12</sup>

Differences in charging times across solar and non-solar owners may be due to the strong financial incentives solar owners have to charge using their generation. However, other differences across the two groups suggest caution in adopting this causal interpretation. For example, non-solar owners are more likely to face a flat electricity price (a tariff that does not vary by time-of-day), rent, be under 35, and have less experience with EV ownership.

To test the impact of incentives, we offered the randomly determined treatment group payments for any difference in charge compared to a baseline, regardless of the location of the charge. We provided two different incentives. First, all owners in the Treatment group earned AUD 0.20 per kWh below their baseline between 4pm–8pm Monday to Friday (peak rewards). This incentive was designed to lower charging when the electricity grid becomes strained and wholesale electricity prices are typically higher. Electricity grids

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<sup>9</sup>In Appendix Tables we show the equivalent tests pooling over solar and non-solar participants, and report a joint orthogonality test (a regression of Treatment on all observable characteristics), univariate balance tests (individual regressions of Treatment on each characteristic), and a balance table for “compliers”.

<sup>10</sup>Median annual household income in Australia is around AUD 92,000 (Australian Bureau of Statistics, 2023).

<sup>11</sup>These chargers are known in the industry as “Level 2” or “wall chargers” and charge at approximately three times the speed of a regular outlet.

<sup>12</sup>Descriptive statistics for the follow-up survey are in the Appendix. As these responses occurred after the experiment ended, we did not test balance.

relying on solar generation become strained due to the combined impacts of an increase in demand and a reduction in solar output.<sup>13</sup> The second incentive, for owners without rooftop solar, is AUD 0.20 for each kWh above their baseline between 10am–3pm Monday to Friday (sun soak rewards). This reward incentivizes charging when solar generation is abundant and wholesale electricity prices are typically lower. We do not provide the same incentive to rooftop solar owners as they face strong incentives to charge at home during the middle of the day when their panels are producing (La Nauze, 2019; Martin, 2022). The incentives faced by the two types of vehicle owners (solar and non-solar) by hour of the day are depicted at the top of Figure 2.

For context, households in Australia on flat tariffs pay AUD 0.25–0.40 per kWh in usage charges.<sup>14</sup> Households with rooftop solar are paid AUD 0.06–0.10 per kWh to export excess electricity (generation not used or stored behind the meter), which is the opportunity cost of charging when they would otherwise export. The sun soak incentive was designed to provide vehicle owners without rooftop solar the same approximate opportunity cost during peak solar generation hours as those with rooftop solar.<sup>15</sup>

Participants’ rewards were calculated for each time-of-day by comparing the total weekly charge in kWh with a weekly participant baseline. The weekly baselines were determined in two steps using pre-trial and trial data. First, for each participant and time-of-day, the mean share of daily charge (Monday–Friday) was calculated using four weeks of pretreatment data (baseline share). Second, for each trial week, total kWh Monday–Friday was computed (weekly kWh). The time-of-day baseline share was then applied to the weekly kWh to compute the weekly time-of-day baseline.<sup>16</sup> At the end of the reward period, the total reward was sent to each participant in a multi-store electronic gift card up to AUD 200.

For our main analysis, we restrict the sample to charging Monday–Friday and estimate the impact of incentives on charging by hour of the day using the following regression:

$$y_{vht} = \alpha_{ih} + \gamma_{st} + \eta_{whm} + T'_{iht}\beta + u_{vht} \quad (1)$$

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<sup>13</sup>These problems are most apparent on weekdays, hence we focus on weekday charging.

<sup>14</sup>Most of Australia has competitive retail electricity markets so prices are not set by regulators (Australian Competition and Consumer Commission ACCC, 2023).

<sup>15</sup>Several retail electricity companies offer variable tariffs of AUD 0.06 per kWh for charging between midnight and 6am. Since our experiment, some introduced offers with AUD 0.00 per kWh for charging between 11am and 2pm, providing incentives similar to our sun soak reward.

<sup>16</sup>To avoid confusion and manipulation, participants were told they would receive rewards for charging relative to their baseline, which was determined using pre-existing charging records. Three participants requested further information and were told how their baselines were calculated. We communicated with participants via an initial email and two update emails during the reward period. Participants could also check their rewards balance, charging history and their weekly baseline via Teslascope. Control group members maintained access to Teslascope but were not informed about the rewards during the trial.

where  $y_{vht}$  is charge (kWh) of vehicle  $v$  in hour  $h$  of date  $t$ ,  $\alpha_{ih}$  is participant  $i$  by hour  $h$  fixed effect (capturing permanent owner charging habits),  $\gamma_{st}$  is a solar  $s$  by date  $t$  fixed effect (capturing different trends in charging over the sample for solar and non-solar owners),  $\eta_{whm}$  is a recruitment wave by hour by calendar month fixed effect (capturing differences in seasonal charging habits for owners, and allowing these to differ by recruitment wave),  $T_{iht}$  is a matrix of Treatment indicators for sun soak and peak rewards for solar and non-solar owners,  $\beta$  is a vector of coefficients, and  $u_{vht}$  is a stochastic error term. We cluster standard errors on participant, the unit of randomization.<sup>17</sup> Our main outcome of interest is charge (kWh) however we also employ the same specification to understand the impact of incentives on when charging starts, and at what battery level charging starts. We also estimate the effect of being in the Treatment group on daily distance, duration, and probability of driving. For daily outcomes, we replace participant-hour fixed effects with participant fixed effects and wave-by-month-by-hour fixed effects with wave-by-month fixed effects.

### 3 Results

An important question in the electrification of transport and the greening of electricity grids is whether incentives can reduce EV charging during peak times when the grid is strained and increase charging at times when solar electricity generation is abundant. To answer this question, we begin with a graphical analysis of charging and incentives over the period February 2023–December 2023.<sup>18</sup> Figure 1 plots normalized charge in kWh for Treatment and Control groups. The vertical line shows the start of randomized incentives to the Treatment group. Panel (a) plots a local polynomial smooth and 95% confidence interval of average hourly charge in kWh during peak hours (4pm–8pm) when owners receive incentives to reduce charge, normalized for each vehicle by pretreatment average peak hourly charge. Panel (b) plots a local polynomial smooth and 95% confidence interval of normalized average hourly charge in kWh for vehicle owners without rooftop solar during sun soak hours (10am–3pm) when they receive incentives to increase charge.

In both panels of Figure 1, Control group charge is gray. In Panel (a) Treatment group charge is green, in Panel (b) Treatment group charge is yellow. The confidence intervals for Treatment and Control overlap in the pre-reward period, showing balance. After rewards commence, Treatment vehicles reduce peak charge and increase sun soak charge relative to Control vehicles. In the Appendix, we present an alternative visualization of the effect of incentives comparing hourly solar and non-solar charging profiles for

<sup>17</sup>Participants with two vehicles in our experiment have the same treatment status.

<sup>18</sup>We restrict to this period as only 37% of the sample are observed before 2023, and January is summer vacation in Australia.

Treatment vehicles before and during the reward period. Before the reward period, rooftop solar owners charge substantially more during midday. Non-solar owners are more likely to charge during the evening. During the reward period, when both groups face similar incentives, the charging profiles follow a similar pattern with peaks at midnight and midday.

To quantify the impact of incentives, Table 2 reports treatment effects estimated using the model in Equation 1. In Column (1), we show peak rewards lead to a reduction of 0.065 kWh per hour between 4pm and 8pm Monday to Friday and sun soak rewards lead to an increase of 0.11 kWh per hour between 10am and 3pm Monday to Friday. In Column (2), where we allow the effect of peak rewards to differ for solar and non-solar owners, peak incentives reduce charging by 0.05 kWh for solar vehicle owners and 0.09 kWh for non-solar vehicle owners, (difference not statistically significant). In the Appendix, we show these results are stable across 14 fixed effect combinations and report sharpened q-values to account for multiple hypothesis testing according to Anderson (2008).

Our estimates indicate substantial flexibility in charging that can support a grid dominated by solar generation. Relative to mean hourly charging, solar owners reduced their peak charge by 17%. Non-solar owners reduced their peak charge by 27% and increased their sun soak charge by 34%. The economic significance of these results to minimizing the cost of the energy transition is notable. Under our reward scheme, it costs AUD 200 to shift 1 MWh from the peak, and a further AUD 200 for non-solar owners to increase consumption by 1 MWh during the sun soak period. For comparison, recent estimates by Lazard (2023) show the levelized cost of energy for utility-scale 4-hour storage ranges from AUD 380 to AUD 487 per MWh, and these values do not include avoided network expansion costs.

We have shown that incentives substantially reduce peak charging and increase midday charging to support a solar-dominated grid. The welfare effects of these incentives also depend on whether vehicle owners substitute from and to untreated hours, and if so, which hours. Figure 2 reports treatment effects for solar vehicle owners (left-hand side) and non-solar vehicles (right-hand side) by hour of the day. The specifications include the same fixed effects as previously. The treatment effects during peak (green area) and sun soak (yellow area) periods are evident. Further, we observe no statistically significant increase in charging outside these hours. Rather, we observe significant additional reductions in charging during non-peak evening hours (9–11pm). The fact that solar owners do not increase charging during the middle of the day when they have access to cheap charging suggests this potential is already fully utilized either because the production from rooftop panels is exhausted, or it is not feasible to utilize it any further (e.g. because cars are not home). Consistent with these findings, in the Appendix, we show a marginally significant

reduction in charging from solar owners across all days, indicating they are also not substituting to weekend charging (when rewards are not earned), but rather that their aggregate charging is somewhat price elastic.<sup>19</sup>

For electricity networks, spikes in charging that result from many vehicles commencing charge at the same interval could also prove costly and are a potential downside of uniform time-of-day incentives. In the final row of Figure 2 we show the effect of incentives on the probability a charge of at least 1 kWh is started by hour of the day. We observe no spikes in charging by solar owners, however, we do observe notable spikes in the number of non-solar owners charging at the start of the sun soak period (10am) and at 8pm when the peak period ends. Incentives starting at staggered intervals might be important to smooth these spikes.

For vehicle owners who commute or drive during the day, charging infrastructure is a potential constraint on midday charging and is therefore important to policy. A novelty of our data and experiment is that we observe and incentivize charging regardless of metering point. To understand the role of incentives on out-of-home charging, in columns (3) and (4) of Table 2 we report the effect of incentives separately for charging at home and out-of-home locations. Home locations are identified as the most common overnight location of the vehicle.<sup>20</sup> In column (3), peak incentives reduce home charging, consistent with owners typically being at home during peak hours but avoiding charging once incentives are introduced. However, sun soak incentives do not affect home charging. In contrast, we see in column (4) that sun soak incentives increase out-of-home charging but peak incentives have no effect. This suggests that access to public or workplace charging infrastructure, combined with incentives to charge, will enhance the ability of EVs to support the transition to a renewable electricity grid by charging at times when solar output is high.

To shed light on mechanisms that may inform targeting and policy, we next explore heterogeneity along key dimensions we expect to predict charging patterns and flexibility: whether an owner had high baseline charging levels, is a commuter, has a fast home charger, or uses scheduling apps to manage their charging.<sup>21</sup> Results are reported in Panel B of Table 2. The effect of peak incentives is similar across all owners. However, the effect of sun soak incentives for non-solar owners depends on owner characteristics. Vehicle owners with high baseline charge (column (1)) have almost twice the response to sun soak incentives (though the difference is not statistically significant). The response of

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<sup>19</sup>Among solar owners, we find non-commuters and those without fast home chargers reduce average charge.

<sup>20</sup>We verify the accuracy of this measure using self-reported postal code.

<sup>21</sup>For consistency we restrict the sample to owners who answered the endline survey across all characteristics.



commuters (column (2)) is also twice as large as non-commuters (the treatment effect for non-commuters is not statistically significant or different from commuters). Commuters may have the flexibility to charge at work, may drive more and have more charge to shift across hours, or their response may differ along other dimensions correlated with commuting. We also observe a significant response to sun soak incentives from owners with fast home chargers (column (3)) but not from those without them. Owners with fast chargers have more than three times the response of those without (difference is statistically significant). For context, a vehicle plugged into a fast home charger can charge 30–40 kWh in the 5 hours of the sun soak period, while the same vehicle plugged into a regular outlet could only charge 11–13 kWh. Finally, we find no difference in the effect of incentives based on whether owners report using automated scheduling. These results suggest that the speed of fast home chargers may be an important source of flexibility in absorbing solar energy at times of peak production, and may be more important than automation.

On average, increases in sun soak charging occur outside the home, yet those who have fast home chargers also charge more during the day in response to incentives. To disentangle the role of home versus out-of-home charging infrastructure, potentially important targets of policy, in Figure 3 we break down the effect of sun soak incentives for commuters and those with fast wall chargers by charge location.<sup>22</sup> In the first row of Column (a), we show that sun soak incentives have no effect on home charging regardless of commuting status, in the second row of Column (a), we show that commuters increase their sun soak charge at out-of-home locations. In the first row of Column (b) we show that owners with fast home chargers increase home charging in response to sun soak incentives, while both types of owners (with and without fast home chargers) increase out-of-home charging (second row of Column b). In summary, both types of charging infrastructure - fast home chargers and out-of-home chargers - appear important for EVs to charge during solar production hours.

The elasticity of battery capacity is a key determinant of the potential to use EVs as storage to support variable renewable generation. A key advantage of our rich data is that we can extend our analysis to this important dimension of behavior. The third row of Figure 3 shows incentives cause owners to let battery levels run lower before they charge their vehicles. In Column (a), we see a significant reduction in battery state-of-charge at the start of a charge for commuters (both solar and non-solar). In Column (b) we similarly see (noisy) reductions in the battery level at the start of a charge which are relatively homogeneous across owners with or without solar and with or without

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<sup>22</sup>Sharpened q-values are reported in the Appendix.

fast home chargers.<sup>23</sup> For context, vehicle owners typically start charging when battery levels are around 60% and finish charging when battery levels are around 80%.<sup>24</sup> Tesla vehicles enable owners to employ preset rules to start charging if battery levels fall below a threshold and stop charging when battery levels exceed a threshold. Our results suggest preset rules for maximum charge may be less flexible or more frequently used than preset rules for when to commence a charge. We find battery levels are 2% points lower when Treatment vehicles commence a charge during weekdays of our reward period. Overall, average daily battery use of 10 kWh is well below the 60% level when the average vehicle commences charging (36 kWh for a 60 kWh battery) suggesting EVs have considerable excess battery capacity that could be made available to the grid.

Finally, as driving contributes to externalities like congestion, it is important to understand if charging incentives also affect driving. In the final row of Figure 3 we show that solar owners reduce driving distance on weekdays and weekends during the reward period, which is consistent with their slight reduction in charging during the rewards period.<sup>25</sup> We find no statistically significant differences in km driven for non-solar owners, suggesting that changes in commuting habits did not drive increases in charging in response to sun soak incentives (if for example, people are more or less likely to drive to work so they can charge during the day).

## 4 Conclusion

Globally, governments are setting targets, introducing subsidies and investing in charging infrastructure to encourage the uptake of EVs as the single most promising means of decarbonizing transportation (IEA, 2024). However, electrification of the vehicle fleet introduces new challenges for electricity grids transitioning to low and no-carbon energy sources. In particular, EV charging could exacerbate peak-load problems and worsen the mismatch between when renewable energy sources are available and when supply is needed. On the flip side, EVs also hold great potential to help solve these problems – if charging responds to market signals regarding scarcity and if EV batteries can be used as distributed storage assets to enhance grid security and smooth variable renewable production.

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<sup>23</sup>In Appendix figures we show the average across all owners at the start and end of a charging event.

<sup>24</sup>Charging batteries above 80% or letting them deplete below 20% has typically not been recommended, though this advice is now outdated.

<sup>25</sup>In the Appendix, we plot similar average impacts on driving duration and show that driving reductions occur mostly on weekends and by approximately 4 km, or around 13% of average daily driving (30 km). Further, we show that households who have “all electric” vehicles respond similarly to households also owning non-electric vehicles (results reported in Appendix tables). Thus the reduction in EV driving does not appear to be a substitution to non EV driving.



In this paper, we have shown that EV charging is highly flexible. In response to incentives, EV owners reduced their charging during peak periods by up to 30%. Further, owners increased their charge by more than 30% in response to incentives to charge in the middle of the day when abundant solar generation is available. Using novel telematics data that tracks all charging and driving events, we found owners responded to incentives along multiple margins - including shifting when they charge, decreasing overall charging and driving, and allowing their batteries to reach lower levels before charging. Owners receiving incentives to increase charging in the middle of the day did so predominantly at chargers outside the home. One exception is owners who had installed fast home chargers, who also increased midday charging at home. Changes in peak charging were dominated by reductions in at-home charging. Overall, we found important dimensions of heterogeneity in the response to midday “sun soak” incentives, but relative homogeneity in responses to peak reduction incentives. Combined, our results suggest incentives have the potential to shape electric vehicle charging so that electrification of transport supports the transition to renewable electricity grids. However, our results also suggest that access to infrastructure in the form of fast home charging and out-of-home charging is likely to be key to realizing this potential.

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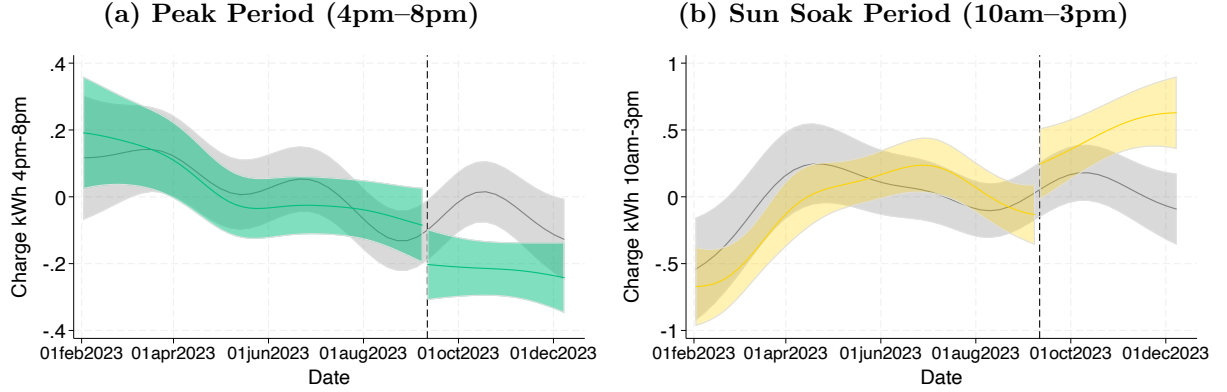
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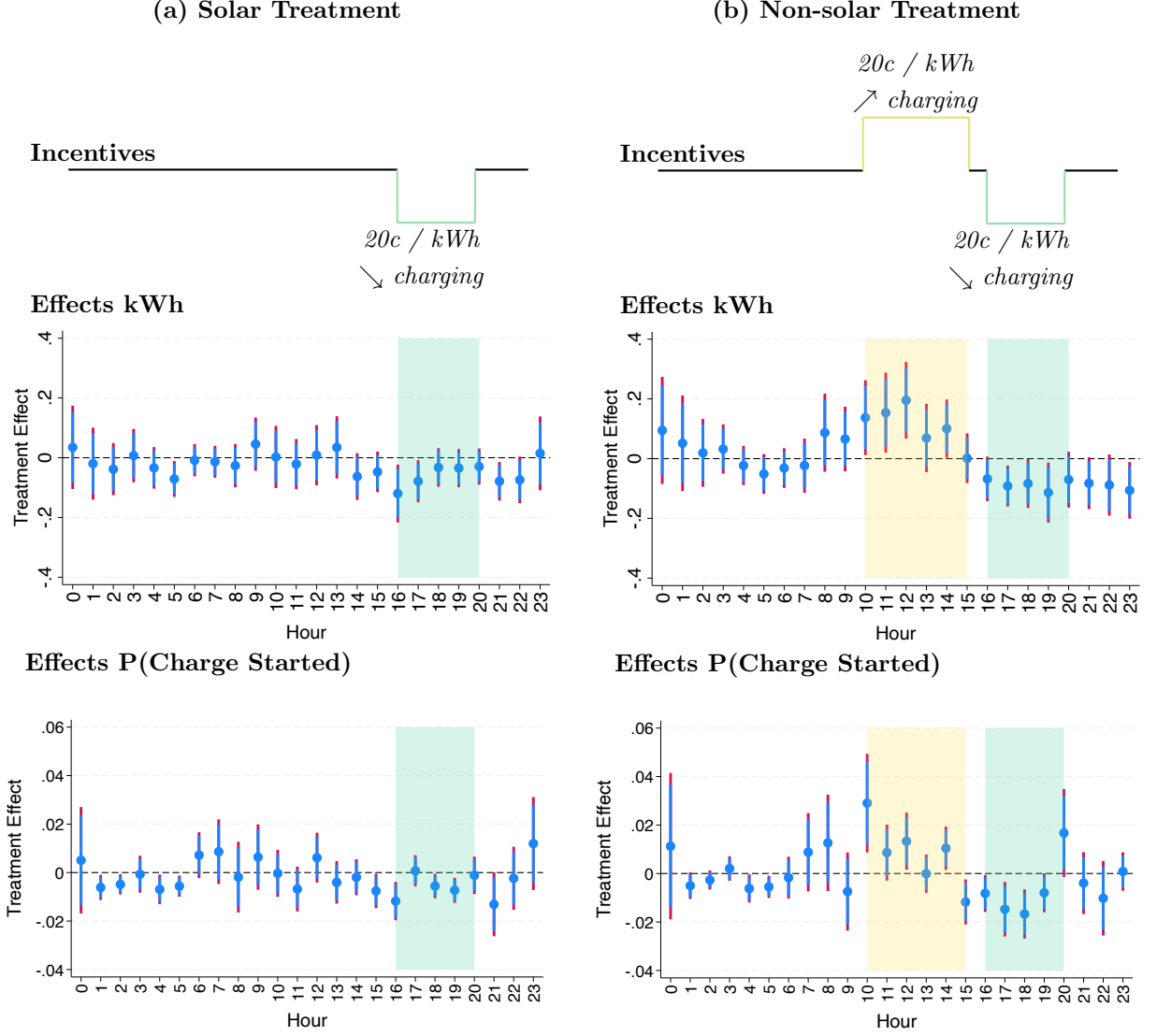
## 5 Figures

Figure 1: Average Hourly Charge (kWh) for Treatment and Control



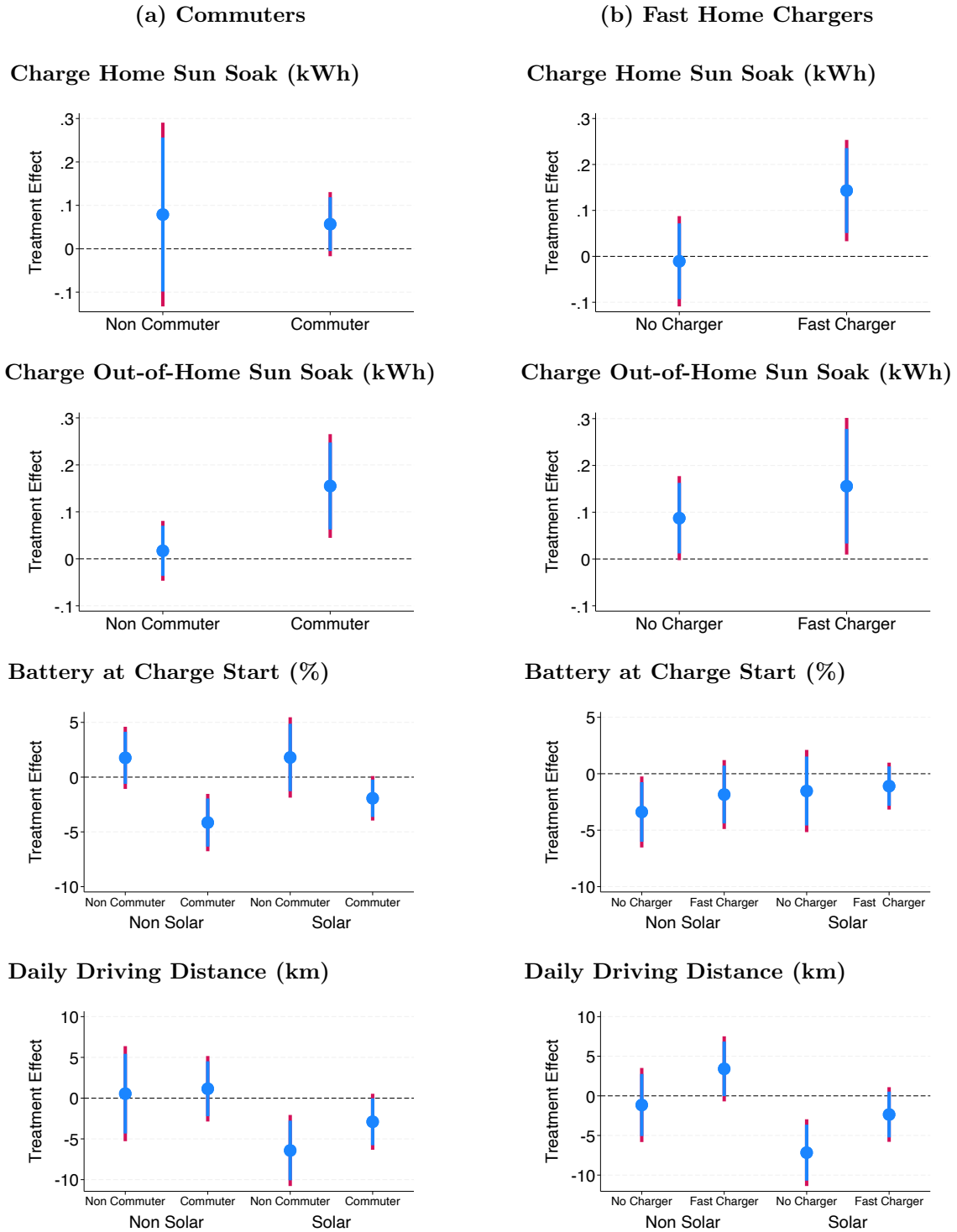
**Notes:** Both panels plot a local polynomial smooth of average hourly charge (kWh) normalized for each vehicle by pretreatment average hourly charge and a 95% confidence interval. Panel (a) plots charge in peak times (4pm–8pm) for Treatment (green) and Control (gray) vehicles. Panel (b) plots charge in sun soak times (10am–3pm) for non-solar Treatment (yellow) and Control (gray). Dashed line represents start of reward period.

Figure 2: Incentives and Treatment Effects by Hour of Day



**Notes:** “Incentives” depicts incentives available to vehicle owners in the treatment group. “Effects kWh” plot estimated effect of incentives on kWh charge for each hour of the day. “Effects P(Charge Started)” plots estimated effects of incentives on the probability a charge is started for each hour of the day. Both 90% (blue) and 95% (red) confidence intervals are plotted. Column (a) plots incentives and effects for the sample of owners with rooftop solar. For most hours of the day, Treatment group members with rooftop solar received no incentive. Between 4pm and 8pm, solar owners received 20c/kWh for each kWh below their individual baseline (peak reduction incentive, green). Column (b) plots incentives and effects for the sample of owners without rooftop solar. Treatment group members without rooftop solar received the peak reduction incentive 4pm–8pm. This group also received 20c/kWh for each kWh above their individual baseline between 10am and 3pm (sun soak incentive, yellow). Specifications include participant-hour fixed effects, solar-by-date fixed effects, and wave-by-month-by-hour fixed effects. Standard errors are clustered by participant.

Figure 3: Additional Treatment Effects



**Notes:** All figures plot estimated treatment effects with both 90% (blue) and 95% (red) confidence intervals. Figures in column (a) report estimated treatment effects by commuting status. Figures in column (b) report estimated treatment effects by whether the owner has a home charger. In row (1) the estimates are the effect of sun soak incentives on hourly charging at home in kWh. In row (2) the estimates are the effect of sun soak incentives on hourly charging not at home in kWh. In row (3) the estimates are the effect of being in the Treatment group on battery levels when a charge begins during rewards days. In row (4) the estimates are the effect of being in the Treatment group on daily driving distance in km on weekdays and weekends. For rows (1)-(3), specifications include participant-hour fixed effects, solar-by-date fixed effects, and wave-by-month-by-hour fixed effects. For row 4, specifications include participant fixed effects, solar-by-date fixed effects and wave-by-month fixed effects. All standard errors are clustered on participant.

## 6 Tables



**Table 1: Descriptive Statistics and Balance**

	Control		Treatment		Difference	
	Mean	SD	Mean	SD	p-val	q-val
<b>Panel A: Solar Vehicle Owners</b>						
Baseline Daily Charge	9.84	6.31	9.50	5.77	0.66	1
Baseline % Peak	0.13	0.15	0.11	0.12	0.15	1
Baseline % Sun Soak	0.44	0.29	0.43	0.29	0.77	1
Baseline % Home	0.65	0.37	0.68	0.39	0.59	1
Baseline Start Battery %	57.73	12.95	60.71	13.64	0.08	1
Baseline End Battery %	81.81	11.13	83.05	10.16	0.36	1
Baseline Daily Distance (km)	29.70	17.62	30.70	19.45	0.67	1
Number of EVs	1.20	0.40	1.18	0.38	0.60	1
Flat Electricity Price	0.45	0.50	0.42	0.50	0.70	1
Renter	0.01	0.09	0.03	0.18	0.18	1
Male	0.58	0.49	0.60	0.49	0.80	1
Aged over 45	0.57	0.50	0.57	0.50	1.00	1
Income > \$130,000	0.60	0.49	0.53	0.50	0.25	1
Home Battery	0.29	0.46	0.31	0.47	0.68	1
Years of EV ownership	2.22	1.74	1.90	1.62	0.13	1
Drivers in Household	2.22	0.77	2.14	0.75	0.45	1
Vehicles in Household	2.14	0.85	2.08	0.79	0.59	1
Observations	125		125		250	
<b>Panel B: Non Solar Vehicle Owners</b>						
Baseline Daily Charge	9.63	5.64	10.18	6.32	0.59	1
Baseline % Peak	0.20	0.18	0.17	0.16	0.41	1
Baseline % Sun Soak	0.22	0.23	0.27	0.26	0.22	1
Baseline % Home	0.58	0.42	0.59	0.44	0.86	1
Baseline Start Battery %	56.64	13.02	58.56	14.19	0.40	1
Baseline End Battery %	84.27	10.96	85.55	10.23	0.47	1
Baseline Daily Distance (km)	29.98	16.74	32.57	20.29	0.41	1
Number of EVs	1.12	0.33	1.09	0.28	0.47	1
Flat Electricity Price	0.56	0.50	0.66	0.48	0.23	1
Renter	0.31	0.47	0.21	0.41	0.18	1
Male	0.64	0.48	0.66	0.48	0.86	1
Aged over 45	0.36	0.48	0.41	0.50	0.49	1
Income > \$130,000	0.57	0.50	0.59	0.50	0.86	1
Home Battery	0.04	0.20	0.09	0.28	0.30	1
Years of EV ownership	1.44	1.46	1.53	1.58	0.74	1
Drivers in Household	1.94	0.81	1.99	0.69	0.74	1
Vehicles in Household	1.87	0.90	1.89	0.75	0.92	1
Observations	70		70		140	

**Notes:** Table reports mean and standard deviation (SD) for Treatment and Control participants as well as the p-value and sharpened q-values for the t-test with null hypothesis that the mean of Treatment and Control are equal. Sharpened q-values account for multiple hypothesis testing. Panel A is for vehicle owners with rooftop solar. Panel B is for vehicle owners without rooftop solar. “Flat Electricity Price” is an indicator for whether a participant’s retail electricity price varies throughout the day.

**Table 2: Effect of Sun Soak and Peak Incentives on Hourly Charge (kWh)**

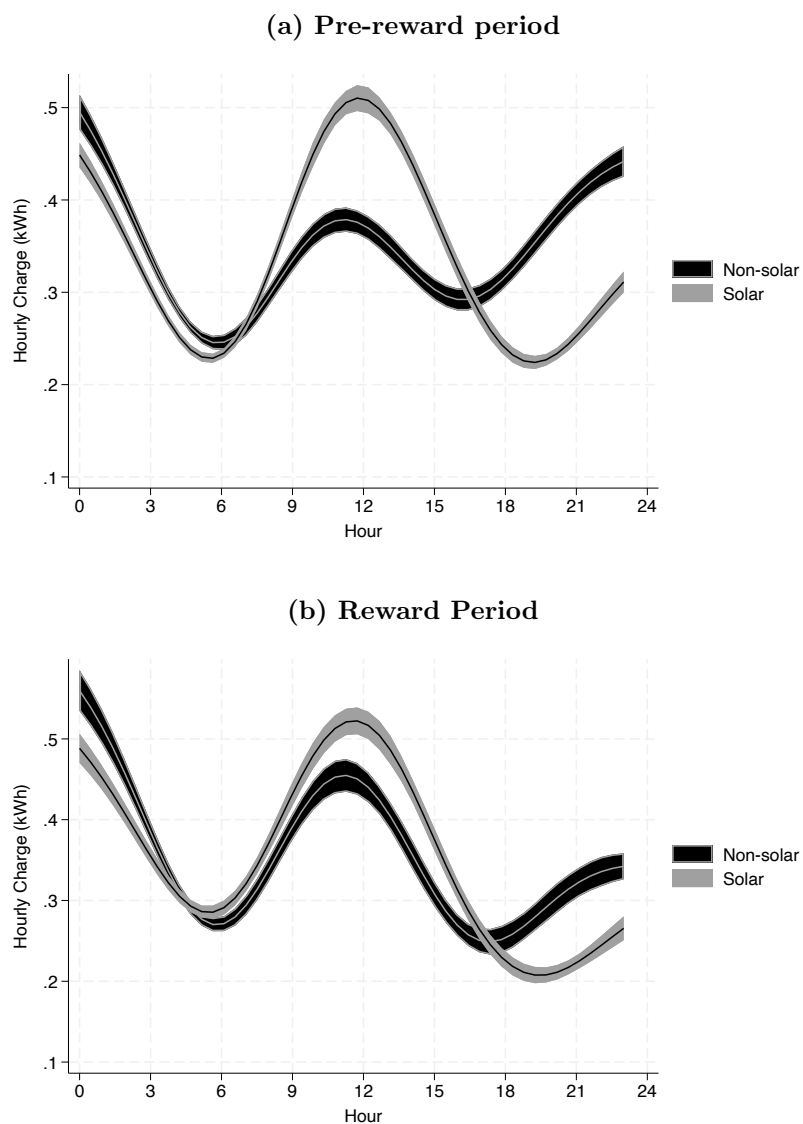
<b>Panel A: Average Effects</b>				
	(1)	(2)	(3)	(4)
		Hourly Charge (kWh)		
			Home	Out-of-Home
Peak Incentive	-0.065*** (0.021)	-0.054** (0.025)	-0.045*** (0.014)	-0.020 (0.017)
Non Solar $\times$ Sun Soak Incentive	0.113** (0.051)	0.110** (0.051)	0.035 (0.033)	0.078** (0.039)
Non Solar $\times$ Peak Incentive		-0.033 (0.033)		
Observations	2813424	2813424	2813424	2813424
DepVar	0.322	0.322	0.178	0.144
<b>Panel B: Heterogeneous Effects</b>				
	(1)	(2)	(3)	(4)
Characteristic =	High Charge	Commuter	Fast Charger	Uses Scheduling
Characteristic=0 $\times$ Peak Incentive	-0.060** (0.023)	-0.084*** (0.032)	-0.067** (0.032)	-0.048 (0.032)
Characteristic=1 $\times$ Peak Incentive	-0.080*** (0.030)	-0.064*** (0.024)	-0.069*** (0.024)	-0.074*** (0.024)
Characteristic=0 $\times$ Non Solar $\times$ Sun Soak Incentive	0.134* (0.070)	0.096 (0.117)	0.077 (0.068)	0.180** (0.082)
Characteristic=1 $\times$ Non Solar $\times$ Sun Soak Incentive	0.250*** (0.091)	0.212*** (0.064)	0.299*** (0.085)	0.184** (0.076)
Observations	2442264	2442264	2442264	2442264
DepVar	0.318	0.318	0.318	0.318

**Notes:** Table reports the average effect of peak reduction and sun soak increase rewards for owners without rooftop solar (receiving both rewards) and owners with rooftop solar (receiving peak reduction rewards only). Panel B reports treatment effects for the following characteristics: whether the participant had high daily charge (kWh) in the pre-reward (baseline) period (column 1), whether the participant commutes to work at least once a week (column 2), whether the participant has installed a fast home charger (column 3) and whether the participant uses a scheduling app to manage charging (column 4). Panel B the sample is restricted to participants who answered the endline survey. Standard errors are clustered on participant. DepVar is the mean of the dependent variable. All specifications include participant-hour fixed effects, solar-by-date fixed effects and wave-by-month-by-hour fixed effects.

## A Appendix

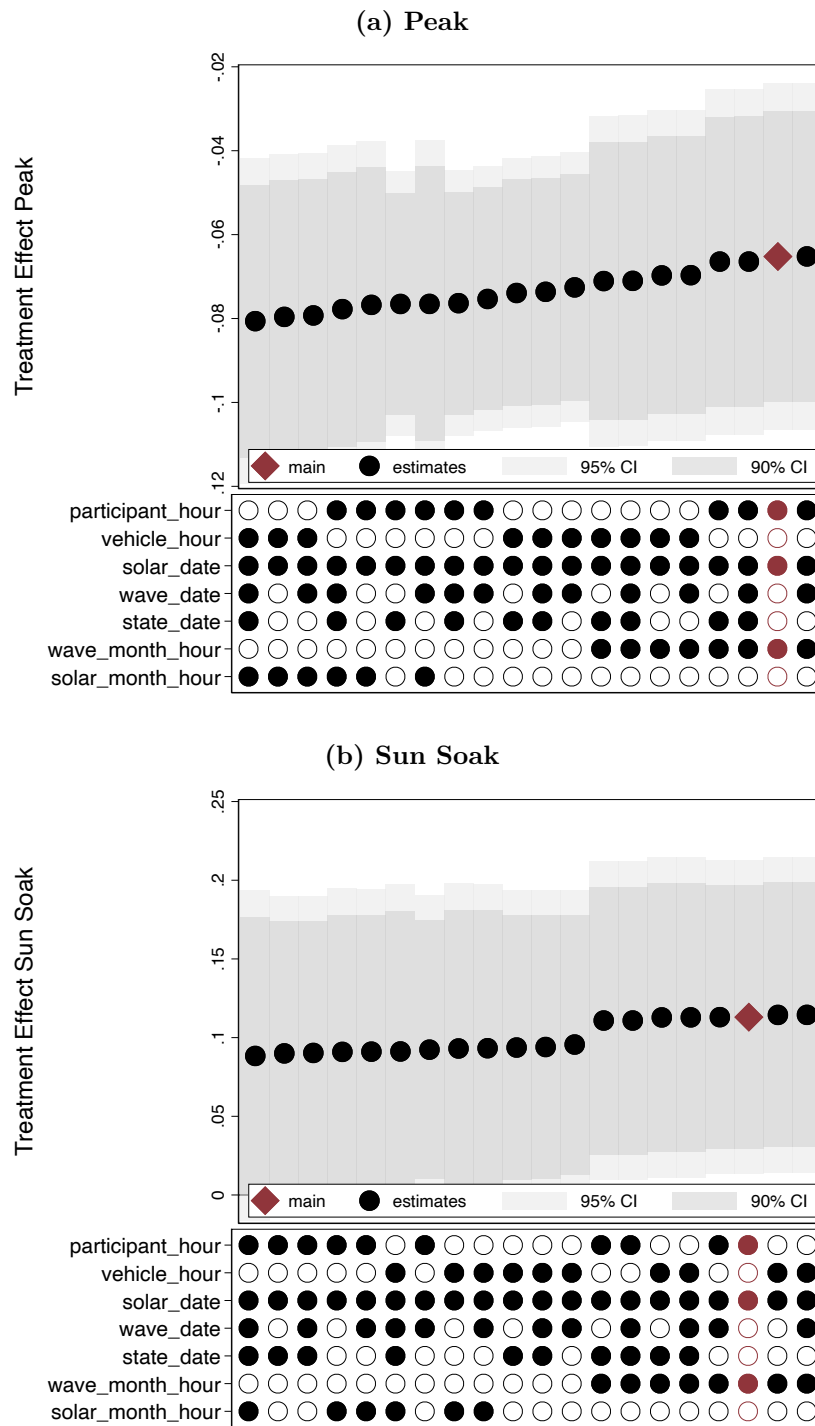
### A.1 Figures

Figure A1: Treatment Group Charging Profiles



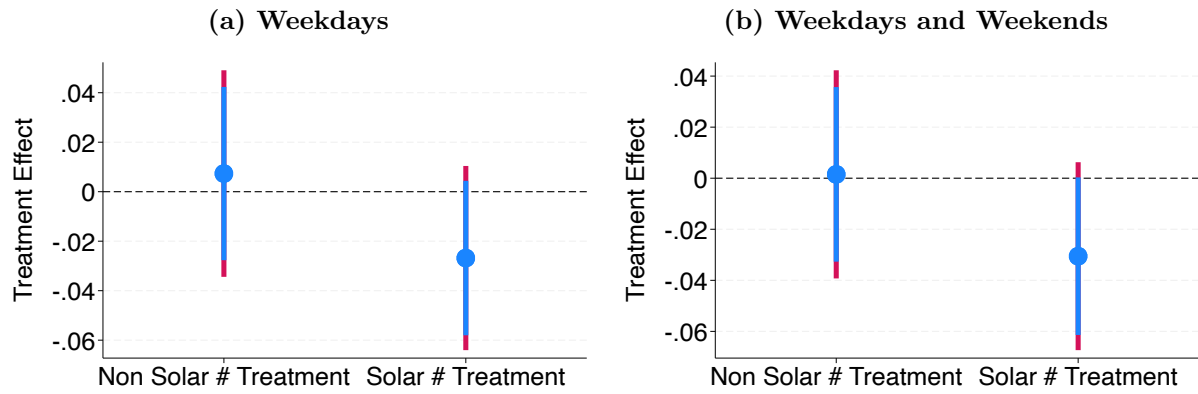
**Notes:** Figures plot local polynomial smooth (and 95% confidence interval) of average hourly charge (kWh) for solar and non-solar Treatment vehicles during (a) February 2023 to the start of the reward period in September 2023 (“pre-rewards” period) and (b) the reward period from September–December 2023.

Figure A2: Treatment Effects with Alternative Fixed Effects



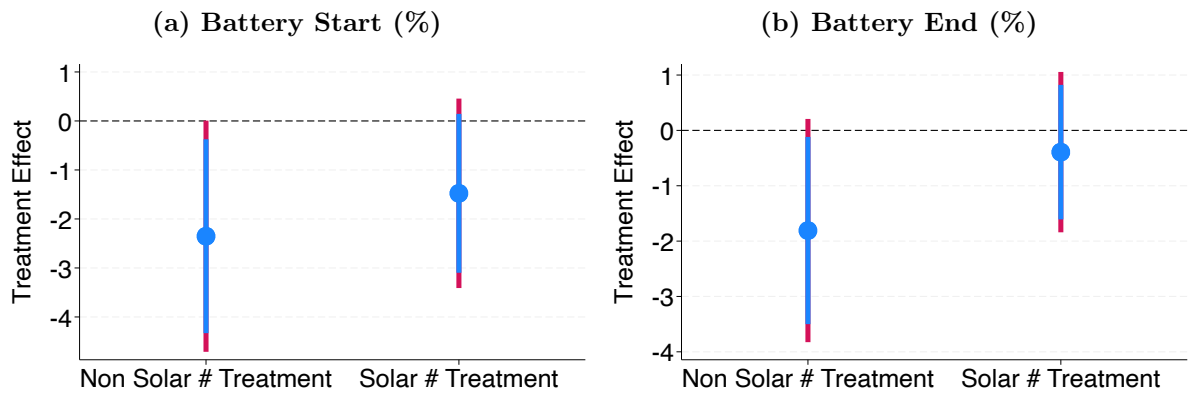
**Notes:** Figure plots treatment effects with 90% (dark gray) and 95% (light gray) confidence intervals. Panel (a) displays the effect of peak rewards. Panel (b) displays the effect of sun soak rewards. Fixed effects for each model are specified in the panel (peak and sun soak effects are estimated in the same regression). The main specification is indicated with a red diamond. Coefficients are sorted by magnitude. Standard errors are clustered on participant.

Figure A3: Hourly Charge Weekdays and Weekends (kWh)



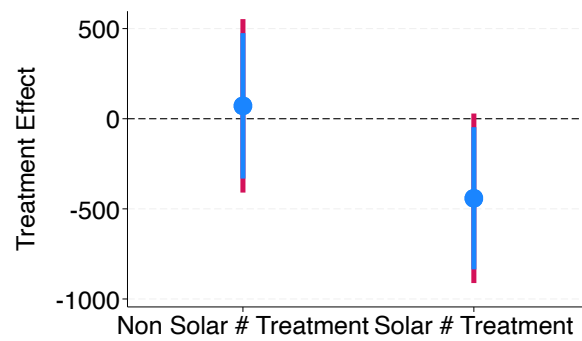
**Notes:** Figure plots the effect of being in the Treatment group on hourly charge on weekdays (panel a) and on all days (panel b) during the reward period for solar and non-solar vehicle owners. Blue lines are 90% confidence intervals, red lines are 95% confidence intervals. Specifications include participant-hour fixed effects, solar-by-date fixed effects, and wave-by-month-by-hour fixed effects. Standard errors are clustered on participant.

**Figure A4: Battery State of Charge (%) On Rewards Days**



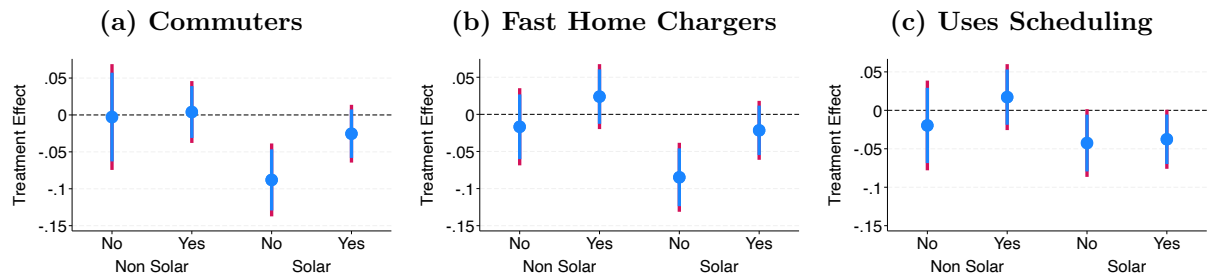
**Notes:** Figure plots the effect of being in the Treatment group on battery state of charge during rewards days at: (a) the beginning of a charge event (b) the end of a charge event. Blue lines are 90% confidence intervals, red lines are 95% confidence intervals. Specifications include participant-hour fixed effects, solar-by-date fixed effects, and wave-by-month-by-hour fixed effects. Standard errors are clustered on participant.

**Figure A5: Drive Duration (sec) Weekdays and Weekends**



**Notes:** Figure plots the effect of being in the Treatment group during the reward period on daily drive duration in seconds on weekdays and weekends for solar and non-solar owners. Blue lines are 90% confidence intervals, red lines are 95% confidence intervals. Specifications include participant fixed effects, solar-by-date fixed effects, and wave-by-month fixed effects. Standard errors are clustered on participant.

**Figure A6: Hourly Charge Weekdays and Weekends (kWh) Heterogeneity**



**Notes:** Figure plots estimated effect of being in the Treatment group on hourly charge during weekdays and weekends in the reward period for owners with or without rooftop solar, who are or are not commuters, who do or do not have a fast home charger, and who do or do not report using automated scheduling. Blue lines are 90% confidence intervals, red lines are 95% confidence intervals. Specifications include participant fixed effects, solar-by-date fixed effects, and wave-by-month fixed effects. Standard errors are clustered on participant.



## A.2 Tables

**Table A1: Balance Test for Pooled Solar and Non Solar**

	Control		Treatment		Difference	
	Mean	SD	Mean	SD	p-val	q-val
Baseline Daily Charge	9.76	6.06	9.74	5.97	0.98	1
Baseline % Peak	0.16	0.16	0.13	0.14	0.11	1
Baseline % Sun Soak	0.36	0.29	0.37	0.29	0.70	1
Baseline % Home	0.62	0.39	0.65	0.41	0.60	1
Baseline Start Battery %	57.34	12.95	59.94	13.85	0.06	1
Baseline End Battery %	82.69	11.11	83.95	10.23	0.24	1
Baseline Daily Distance (km)	29.80	17.27	31.38	19.72	0.40	1
Number of EVs	1.18	0.38	1.15	0.35	0.42	1
Flat Electricity Price	0.49	0.50	0.51	0.50	0.69	1
Renter	0.12	0.32	0.10	0.30	0.52	1
Male	0.60	0.49	0.62	0.49	0.76	1
Aged over 45	0.49	0.50	0.51	0.50	0.69	1
Income > \$130,000	0.59	0.49	0.55	0.50	0.41	1
Home Battery	0.20	0.40	0.23	0.42	0.46	1
Years of EV ownership	1.94	1.68	1.77	1.61	0.30	1
Drivers in Household	2.12	0.79	2.09	0.73	0.69	1
Vehicles in Household	2.04	0.88	2.01	0.78	0.71	1
Observations	195		195		390	

**Notes:** Table reports mean and standard deviation (SD) for Treatment and Control participants as well as the p-value and sharpened q-values for the t-test with null hypothesis that the mean of Treatment and Control are equal. Sharpened q-values account for multiple hypothesis testing. “Flat Electricity Price” is an indicator for whether a participant’s retail electricity price varies throughout the day.

**Table A2: Balance Test for Pooled Solar and Non Solar Compliers Only**

	Control		Treatment		Difference	
	Mean	SD	Mean	SD	p-val	q-val
Baseline Daily Charge	9.65	6.01	9.56	5.77	0.88	1
Baseline % Peak	0.15	0.16	0.13	0.14	0.15	1
Baseline % Sun Soak	0.37	0.29	0.38	0.29	0.72	1
Baseline % Home	0.62	0.39	0.64	0.41	0.81	1
Baseline Start Battery %	57.41	12.93	60.24	13.64	0.04	1
Baseline End Battery %	82.70	11.19	84.15	10.28	0.19	1
Baseline Daily Distance (km)	29.35	17.05	30.66	18.56	0.48	1
Number of EVs	1.18	0.38	1.15	0.36	0.43	1
Flat Electricity Price	0.48	0.50	0.51	0.50	0.57	1
Renter	0.11	0.32	0.10	0.30	0.75	1
Male	0.59	0.49	0.63	0.48	0.49	1
Aged over 45	0.49	0.50	0.50	0.50	0.88	1
Income > \$130,000	0.59	0.49	0.55	0.50	0.44	1
Home Battery	0.21	0.41	0.23	0.42	0.69	1
Years of EV ownership	1.97	1.70	1.77	1.60	0.25	1
Drivers in Household	2.11	0.80	2.09	0.74	0.74	1
Vehicles in Household	2.04	0.88	2.00	0.79	0.67	1
Observations	188		187		375	

**Notes:** Table reports mean and standard deviation (SD) for Treatment and Control participants who remain in the sample throughout the reward period as well as the p-value and sharpened q-values for the t-test with null hypothesis that the mean of Treatment and Control are equal. Sharpened q-values account for multiple hypothesis testing. “Flat Electricity Price” is an indicator for whether a participant’s retail electricity price varies throughout the day.

**Table A3: Joint Orthogonality Balance Test**

	(1)
	(mean) Treatment
Baseline Daily Charge	-0.007 (0.010)
Peak Baseline Share	88 -0.290 (0.197)
Sun Soak Baseline Share	-0.014 (0.119)
Home Baseline Share	08 -0.011 70 (0.069)
Baseline Start Battery %	0.003 (0.003)
Baseline End Battery %	0.001 (0.003)
Baseline Daily Distance (km)	0.003 (0.003)
Number of EVs	-0.010 (0.087)
Flat Electricity Price	0.035 (0.057)
Renter	-0.059 (0.095)
Male	0.028 (0.077)
Aged over 45	0.014 (0.056)
Income > \$130,000	-0.035

	(0.056)
Home Battery	0.079 (0.070)
Years of EV ownership	-0.012 (0.020)
Drivers in Household	-0.001 (0.052)
Vehicles in Household	-0.015 (0.048)
Constant	0.386 (0.313)
Observations	389
p-val	0.846

**Notes:** Table reports results of regressing the treatment assignment variable on observable characteristics at the owner level. “p-val” reports the p-value for the test of joint significance. “Flat Electricity Price” is an indicator for whether a participants retail electricity price varies throughout the day. Standard errors in parentheses.

**Table A4: Univariate Balance Tests**

Baseline Daily Charge	
Treatment=1	-0.022 (0.378)
Observations	390
Peak Baseline Share	
Treatment=1	-0.024 (0.015)
Observations	390
(1)	
Sun Soak Baseline Share	
Treatment=1	0.011 (0.025)
Observations	390
Home Baseline Share	
Treatment=1	0.021 (0.041)
Observations	390
Baseline Start Battery %	
Treatment=1	2.575* (1.312)
Observations	390
Baseline End Battery %	
Treatment=1	1.245 (1.047)
Observations	390
Baseline Daily Distance (km)	
Treatment=1	1.643 (1.414)
Observations	389
Number of EVs	
Treatment=1	-0.030 (0.036)
Observations	390
Flat Electricity Price	
Treatment=1	0.023

	(0.050)
Observations	390
<hr/>	
	(1)
	Renter
Treatment=1	-0.020
	(0.029)
Observations	390
<hr/>	
	Male
Treatment=1	0.015
	(0.036)
Observations	390
<hr/>	
	Aged over 45
Treatment=1	0.022
	(0.050)
Observations	390
<hr/>	
	Income > \$130,000
Treatment=1	-0.042
	(0.050)
Observations	390
<hr/>	
	Home Battery
Treatment=1	0.032
	(0.040)
Observations	390
<hr/>	
	Years of EV ownership
Treatment=1	-0.177
	(0.153)
Observations	390
<hr/>	
	Drivers in Household
Treatment=1	-0.029
	(0.077)
Observations	390
<hr/>	
	Vehicles in Household
Treatment=1	-0.029
	(0.083)
Observations	390
<hr/>	

**Notes:** Table reports results of separate regressions of the treatment assignment variable on each observable characteristic at the owner level. “Flat Electricity Price” is an indicator for whether a participant’s retail electricity price varies throughout the day. Standard errors in parentheses.

**Table A5: Endline Renewal Survey**

	Mean	SD
Has Wall Charger	0.635	0.482
Uses Scheduling	0.746	0.436
Can Charge at Work	0.263	0.441
Commuter	0.802	0.399
Observations	323	

**Notes:** Table reports mean and standard deviation (SD) of indicator variables for whether owners self-report in the endline survey that they have a fast home charger at home, use automated scheduling, can charge their vehicle at work, or are a commuter.



**Table A6: p-values and sharpened q-values for Table 2**

<b>Panel A: Average Effects</b>					
		(1)	(2)	(3)	(4)
			Hourly Charge (kWh)		
				Home	Out-of-home
Peak Incentive	p val	0.002	0.032	0.001	0.247
	q val	0.005	0.051	0.003	0.141
Non Solar Sun Soak Incentive	p val	0.026	0.031	0.297	0.046
	q val	0.014	0.051	0.175	0.102
Non Solar Peak Incentive	p val		0.326		
	q val		0.122		
<b>Panel B: Heterogeneous Effects</b>					
		(1)	(2)	(3)	(4)
			Hourly Charge (kWh)		
		High Charge	Commuter	Fast Charger	Uses Scheduling
Characteristic =					
Characteristic = 0 $\times$ Peak Incentive	pval	0.010	0.009	0.038	0.137
	qval	0.011	0.01	0.026	0.041
Characteristic = 1 $\times$ Peak Incentive	pval	0.008	0.007	0.004	0.002
	qval	0.011	0.01	0.007	0.009
Characteristic = 0 $\times$ Non Solar	pval	0.055	0.412	0.261	0.029
$\times$ Sun Soak Incentive	qval	0.011	0.115	0.07	0.03
Characteristic = 1 $\times$ Non Solar	pval	0.007	0.001	0.001	0.016
$\times$ Sun Soak Incentive	qval	0.011	0.005	0.005	0.025

**Notes:** Table reports p-values and sharpened q-values that account for multiple hypothesis testing within each regression. Both p-values and q-values refer to the single null hypothesis that the corresponding coefficient in Table 2 is zero.

**Table A7: p-values and sharpened q-values for rows 1 - 2 of Figure 3**

		(1)	(2)	(3)	(4)
		Hourly Charge (kWh)			
Characteristic =		Commuter		Fast Charger	
		Home	Out-of-home	Home	Out-of-home
Characteristic = 0 × Non Solar	pval	0.464	0.599	0.830	0.057
× Sun Soak Incentive	qval	0.359	0.428	0.71	0.061
Characteristic = 1 × Non Solar	pval	0.132	0.006	0.011	0.037
× Sun Soak Incentive	qval	0.359	0.013	0.023	0.061

**Notes:** Table reports p-values and sharpened q-values that account for multiple hypothesis testing within each regression. Both p-values and q-values refer to the single null hypothesis that the corresponding coefficient in Figure 3 is zero.

**Table A8: p-values and sharpened q-values for rows 3-4 of Figure 3**

		(1)	(2)
		Battery Charge	Start (%)
Characteristic =		Commuter	Fast Charger
Characteristic = 0 × Non Solar	pval	0.223	0.035
	qval	0.175	0.163
Characteristic = 0 × Solar	pval	0.336	0.409
	qval	0.202	0.443
Characteristic = 1 × Non Solar	pval	0.002	0.236
	qval	0.009	0.429
Characteristic = 1 × Solar	pval	0.062	0.300
	qval	0.103	0.429
		(1)	(2)
		Drive Distance	(km)
Characteristic =		Commuter	Fast Charger
Characteristic = 0 × Non Solar	pval	0.853	0.627
	qval	0.744	0.316
Characteristic = 0 × Solar	pval	0.004	0.001
	qval	0.017	0.005
Characteristic = 1 × Non Solar	pval	0.574	0.103
	qval	0.62	0.183
Characteristic = 1 × Solar	pval	0.098	0.180
	qval	0.173	0.22

**Notes:** Table reports p-values and sharpened q-values that account for multiple hypothesis testing within each regression. Both p-values and q-values refer to the single null hypothesis that the corresponding coefficient in Figure 3 is zero.

**Table A9: Effect on Driving - All Electric vs Mixed Vehicle Households**

	(1)	(2)	(3)
	Duration	Distance	Drives
Mixed Vehicles $\times$ Treatment	-384.530 (248.526)	-2.301 (1.716)	-0.025 (0.025)
All Electric $\times$ Treatment	-562.831 (344.697)	-2.409 (2.521)	-0.033 (0.037)
Observations	109641	109641	109641
DepVar	4151.313	27.058	0.700

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ 

**Notes:** Table reports results of the regression of daily driving duration in seconds (column 1), distance in kilometres (column 2), and the probability of driving on Treatment group status interacted with an indicator for whether all the vehicles of the household are observed in the sample. DepVar is the mean of the dependent variable. All specifications include participant fixed effects, solar-by-date fixed effects and wave-by-month fixed effects. Standard errors in parentheses are clustered by participant.

**Table A10: Effect on Weekday vs Weekend Driving - Solar Households**

	(1)	(2)	(3)
	Duration	Distance	Drives
weekend=0 $\times$ Treatment	-341.100 (254.520)	-1.614 (1.757)	-0.022 (0.024)
weekend=1 $\times$ Treatment	-715.764** (293.095)	-4.291* (2.192)	-0.041 (0.025)
Observations	109641	109641	109641
DepVar	4151.313	27.058	0.700

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Notes:** Table reports results of regression of daily driving duration in seconds (column 1), distance in kilometres (column 2), and the probability of driving on Treatment group status for solar owners. DepVar is the mean of the dependent variable. All specifications include participant fixed effects, solar-by-date fixed effects, and wave-by-month fixed effects. Standard errors in parentheses are clustered by participant.