Electric Vehicle Managed Charging Experiment: Pre-Analysis Plan

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July 11, 2024

Abstract

In this project, we partner with Peninsula Clean Energy, a California electric utility, to evaluate the impacts of experimental electricity price schedules and control technology for electric vehicle (EV) owners on household electricity use. Electrified transportation is a critical component of global decarbonization plans; beyond reducing greenhouse gas emissions from driving, EVs may also balance intermittent renewables by providing battery services to the grid. The ability to realize these benefits depends on two factors: 1) how EV owners respond to the pricing incentives that align private and social marginal costs of electricity consumption, and 2) EV owners' willingness to allow utilities to directly manage their charging load. We use a randomized controlled trial to estimate consumers' willingness to accept novel rates, including time-of-use price schedules and managed charging plans where consumers cede control over their charging to the utility. We will then quantify the impacts of these experimental electricity pricing plans on the timing and amount of EV electricity consumed.

1 Introduction

Policymakers in the United States and around the world are pursuing a climate change strategy based on two principles: (i) decarbonization of the electricity grid and (ii) mass electrification of energy services. Transportation is a cornerstone of this vision: vehicle electrification is a major policy goal, with bans on the sale of new internal combustion engine (ICE) cars announced in France and the UK (2040), Norway (2025), India (2030), China (timing not yet announced) and, most recently, California (2035). Despite these goals, surprisingly little is known about the determinants of electric vehicle (EV) adoption and utilization. While there has been a large

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amount of research on the elasticity of ICE usage with respect to gasoline prices, it has proven difficult to even quantify driving behavior on the part of EV owners, let alone how they respond to incentives.

As more and more EVs are added to the electricity grid, they pose new challenges, highlighted by our prior work (Burlig et al. (2021)). First, EVs use a substantial amount of electricity. Because, absent additional policy, this energy use tends to be concentrated in time, this may necessitate substantial and costly upgrades to existing grid infrastructure. Second, absent further intervention, EVs are typically charged during periods of high marginal emissions, undermining their local pollution and climate benefits.

In this project, we use a randomized controlled trial, implemented by Peninsula Clean Energy (PCE), a "community choice aggregator" selling electricity to consumers in Sam Mateo, California, just south of San Francisco. We will use this RCT to evaluate the impact of two approaches to adjusting the timing of EV charging. First, we will estimate the impact of time-of-use (TOU) electricity pricing plans, where customers face different electricity prices at different times of day (e.g. Fowlie et al. (2021)), that apply either to the entire household or just to the EV on household (and EV) energy use. TOU pricing can align EV owners' incentives with grid operators' and reduce marginal emissions.

Second, we measure the effects of "managed charging" on energy usage. Managed charging is a form of partial automation: the electric utility has control over when a customer's EV is charged. Managed charging plans have the potential to be privately and socially valuable. Research has shown that cost-effectively decarbonizing the electricity grid depends on a policymaker's ability to shift consumption to match renewable output (Imelda et al. (2018), Holland et al. (2016)). Managed charging enables an electric utility to optimize consumption across large numbers of households. However, ceding control to the utility may also impose substantial costs on consumers. We will estimate customers' willingness to accept managed charging, as well as quantifying the frequency of consumer overrides while on a managed charging plan.

The remainder of this document outlines our experimental design, data, and planned analyses.

2 Experimental design and data

The experimental sample was drawn from PCE's customer base. All customers who met two criteria were automatically included in the experiment:

1: Electricity rate In order to participate in the experiment, for logistical reasons, customers needed to be on either the E-TOU-C time-of-use electricity rate plan or the EV2A EV electricity rate plan at the time of randomization.

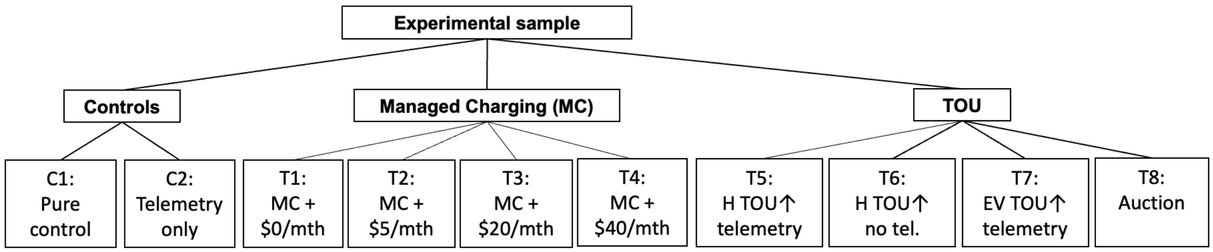
2: EV ownership Households also needed to own an EV at the time of randomization to be enrolled in the experiment. PCE identified households as EV owners if they either (i) were enrolled in the EV2A electricity rate, and/or (ii) if their PCE billing address appeared as the registration address of an EV according to California Department of Motor Vehicles data obtained by PCE.

The final experimental sample consists of approximately 15,000 households. Households were randomly assigned to one of 10 experimental arms, shown in Figure 1, and described below. The randomization was stratified by electricity rate (E-TOU-C or EV2A) and EV type (Tesla, PHEV, other BEV).

2.1 Experimental design

- **C1, Pure control:** No intervention
- **C2, Telemetry only:** Invited to participate in a pilot program that monitored (but did not manipulate) their EV usage patterns via an app.
- **T1, Managed charging, $0/mth:** Invited to participate in the managed charging program with no financial incentive. Includes the same telemetry as in C2. Households who enroll

Figure 1: Experimental Design: Control & Treatment Cells



in the managed charging program install an app, which they link to their vehicle. Whenever the vehicle is plugged into the home meter, the vehicle's charging may be managed (i.e., charging times controlled externally). The charging algorithm adjusts charging according to four priorities: ensuring the vehicle is charged by a driver's preferred "ready by" time; reducing the household's electricity costs according to their rate; and reducing carbon intensity using information on marginal grid emissions.

- **T2, Managed charging, $5/mth:** Same as T1 but with $5/month participation incentive.
- **T3, Managed charging, $20/mth:** Same as T1 but with $20/month participation incentive.
- **T4, Managed charging, $40/mth:** Same as T1 but with $40/month participation incentive.
- **T5, House steep TOU + telemetry:** Household load was exposed to a steepened time-of-use rate, where the off-peak price is reduced by $0.05 / kWh, and on-peak price is increased by $0.05 / kWh, and includes plus the same telemetry as in C2.[1]
- **T6, House steep TOU + no telemetry:** Household load was exposed to the same steepened time-of-use rate as in T5, but no monitoring of EV usage.
- **T7, EV-only steep TOU:** EV charging load was exposed to a steepened time-of-use rate, where pricing adjustments were made using vehicle telemetry data. The price adjustments follow those in T5.

[1]For households on the E-TOU-C rate, the peak periods are 4-9PM every day of the week, and the off-peak periods are 9PM to 4PM. For households on the EV2A rate, the peak period is 4-9PM, the partial peak periods are 3-4PM and 9PM-midnight, and the off-peak is midnight-3PM every day of the week.

- **T8, Managed charging auction:** Online BDM-style process used to elicit WTA for managed charging program.

2.2 Data collection

The data are collected from multiple sources:

1. **Utility electricity meter data:** These utility-provided data are comprised of hourly electricity meter readings in kilowatt-hours (kWh). Coverage includes all electricity meters of households enrolled in the experiment, and contains data for the 12-24 months before the experiment commenced and extends until after the end of the experimental period. These data include unique household identifiers that allow for linkage to the other data sets.
2. **Utility billing data:** This utility-provided dataset includes aggregate monthly kWh and billed amount for each household in the experiment over a period that extends from 12-24 months before the experiment began through the end of the experiment. This is also where customer account information is provided, including electricity rate class, zip code of residence and, once again, unique household identifier.
3. **Telemetry data:** These data record information about all of the EV charging instances for households in groups C2 and T1-T5. These data were collected by the third-party telemetry company and include time and duration of each charging instance, as well as the location (home or away from home). If the household is in a managed charging treatment cell, these data also record when households override the charging management attempt by the utility.

3 Hypotheses and Analysis

3.1 Take-up of experimental offers

As described in Section 2.1, subjects were exposed to some combination of EV telemetry, EV managed charging, and a steeper gradient in whole-house or EV TOU pricing. Participation incentives included participation in lotteries with monetary payouts (all cells with the exception of C1), and monthly bill credits (T1-T4). Households made different decisions depending on their treatment cell, per the reality of actual enrollment decisions in these types of programs.

Both telemetry (C2, T1-T5, T7) and managed charging (T1-T4) were opt-in, because consumers needed to connect their vehicles to the app to participate. Whole-house steep TOU (T5, T6) was opt-out, as would be the standard approach when PCE adjusts rates.[2] EV-only steep TOU was opt-in, because telemetry measurements were required to provide households with EV-specific pricing. Households who opt in to any program are able to opt out at any time.

We therefore estimate the impact of our treatment offers on participation in telemetry with the following specification:

$$Telemetry_i = \beta_0 + \sum_{k \in K} \beta_k T_{i,k} + \eta_s + \varepsilon_i,$$

where $Telemetry_i$ is an indicator for whether household i enrolled in telemetry, $T_{i,k}$ are indicators for being randomized into treatment group $k \in K = \{C2, T1, T2, T3, T4, T5, T7\}$.[3] η_s are strata fixed effects, and ε_i is an error term.

Finally, we estimate "full take-up," which measures whether a household is enrolled in all options it is offered:

$$FullTakeUp_i = \beta_0 + \sum_{k \in K} \beta_k T_{i,k} + \eta_s + \varepsilon_i,$$

where $FullTakeUp_i$ is an indicator for "take-up" of household i's bundle of options (e.g., par-

[2] Note that households in T5 were still automatically exposed to the whole-house TOU treatment, even if they did not enroll in the telemetry measurements.

[3] We exclude T8 from the regressions, because though we randomized people into this arm, engagement with the auction was low enough as not to be useful.

ticipation in whole-house TOU pricing and telemetry for group T5), and all other terms are defined as above. Here, $K = \{C2, T1, T2, T3, T4, T5, T6, T7\}$.

This specification is particularly important in this setting because it allows us to estimate the share of households willing to participate in telemetry only (by comparing C2 to C1), and then estimate the WTA curve for managed charging participation by comparing C1–T4.

Because the experiment lasts for several months, we have an opportunity to measure disenrollment from the program. Therefore, our main take-up variables will be these outcomes in the first month of the experiment. To measure disenrollment, we will estimate these take-up equations again in the final month of the experiment. We also plan to measure the correlation between households' experiences with the program and disenrollment, to the extent that this occurs.

Finally, we will also estimate heterogeneous treatment effects on enrollment by pre-period load profile, pre-period total electricity consumption, and EV type (i.e., Tesla, non-Tesla BEV, PHEV).

3.2 Effects on whole-house electricity usage

Aggregated across all hours-of-day We begin by pooling all managed charging offer groups (T1, T2, T3, T4), whole-house TOU offer groups (T5, T6), and EV-only TOU groups (T7):

$$
\begin{aligned}
kWh_{it} = {} & \beta_1 \mathbf{1}[\text{Managed charging offer}]_{it} + \beta_2 \mathbf{1}[\text{Whole-house TOU offer}]_{it} \\
& + \beta_3 \mathbf{1}[\text{EV-only TOU offer}]_{it} + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it},
\end{aligned}
$$

As a secondary test, we will also estimate the effects of each separate treatment arm on whole-house electricity consumption:

$$kWh_{it} = \sum_{k \in K} \beta_k T_{it,k} + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it},$$

where kWh_{it} is household i's electricity consumption in hour-of-sample t, $\sum_{k \in K} \beta_k T_{it,k}$ is an indicator for being randomized into treatment group $k \in K = \{T1, T2, T3, T4, T5, T6, T7\}$, equal to one only after the experiment has begun for household i, α_i are household fixed effects, δ_m are month-of-sample fixed effects, δ_d are day-of-week fixed effects, δ_h are hour-of-day fixed effects, and ε_{it} is an error term, clustered at the household level. We will also estimate a version with $log(kWh_{it})$ as the dependent variable.

Finally, we will instrument for whole-house TOU take-up, EV-only TOU take-up, and managed charging take-up using the offers, in order to estimate LATEs.

Hour-of-day specific estimates Once again, we begin by pooling all managed charging offer groups (T1, T2, T3, T4), whole-house TOU offer groups (T5, T6), and EV-only TOU groups (T7), and disaggregate the dependent variable to hour-of-sample:

$$\begin{aligned} kWh_{ith} = \sum_{h=0}^{23} \beta_1^h \mathbf{1}[\text{Managed charging offer}]_{it} \times 1[hour = h] + \beta_2^h \mathbf{1}[\text{Whole-house TOU offer}]_{it} \times 1[hour = h] \\ + \beta_3^h \mathbf{1}[\text{EV-only TOU offer}]_{it} \times 1[hour = h] + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it}, \end{aligned}$$

We will also estimate the effects of each separate treatment arm on hourly household electricity consumption:

$$kWh_{it} = \sum_{k \in K} \sum_{h=0}^{23} \beta_k^h T_{it,k} \times 1[hour = h]_h + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it},$$

where we now estimate separate coefficients (β_k^h) by hour of day, and all other terms are defined as above (with $k \in K = \{T1, T2, T3, T4, T5, T6, T7\}$). We will also estimate a version with

$log(kWh_{it})$ as the dependent variable.

In addition, we will also estimate heterogeneous treatment effects on aggregate and hour-specific electricity consumption by pre-period load profile, pre-period total electricity consumption, and EV type (i.e., Tesla, non-Tesla BEV, PHEV).

Price elasticities We estimate the price elasticity of demand using random assignment to steep TOU pricing. First, we restrict the sample to C1, C2, T5, and T6 (control and whole-house TOU groups only) and estimate:

$$log(kWh)_{it} = \beta log(Price)_{it} + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it},$$

where $log(Price)_{it}$ is the marginal price of electricity consumption for household i in hour-of-sample t. We instrument for price with the randomly-assigned steep-TOU offer (i.e., an indicator for being either in T5 or T6). Next, to estimate the price elasticity of whole-house electricity demand with respect to TOU pricing *that applies only to a household's EV*, we restrict the sample to C1, C2, and T7, and re-estimate Equation (1), instrumenting for price with an indicator for being in T7.

3.3 Effects on charging-related decisions

EV charging As a set of secondary outcomes, we are interested in the impacts of our treatment on EV charging behavior. An important caveat with these estimates is that our data on EV charging comes from the telemetry product.[4] As a result, we expect that there may be differential selection into telemetry by treatment arm. We therefore interpret these estimates with caution. Nevertheless, we restrict our sample to households who enroll in telemetry in C2, T1, T2, T3, T4, T5, and T7, and estimate associations between treatment offers and EV charging-

[4]That is, we only observe EV charging for households that are enrolled in telemetry. Because the main empirical objects of interest for this study are program participation and whole-house electricity consumption, we did not randomize households *after* they had agreed to participate in the telemetry measurements.

related outcomes, pooled across offer types:

$$y_{it} = \beta_1 \mathbf{1}[\text{Managed charging offer}]_{it} + \beta_2 \mathbf{1}[\text{Whole-house TOU offer}]_{it}$$
$$+ \beta_3 \mathbf{1}[\text{EV-only TOU offer}]_{it} + \delta_m + \delta_d + \delta_h + \varepsilon_{it},$$

And separate effects for each treatment arm (not pooling offers by type):

$$y_{it} = \sum_{k \in K} \beta_k T_{it,k} + \delta_m + \delta_d + \delta_h + \varepsilon_{it},$$

For both specifications, our outcomes of interest include: total EV charging, EV charging at the home meter, EV charging away from the home meter, and an indicator for whether the managed charging plan is being overridden. We exclude household fixed effects from these specifications, as we only observe EV-charging-related outcomes *after* treatment begins. All other terms are the same as above.

To assess the degree of selection into telemetry, we will check balance between households that do and do not enroll in telemetry in these groups. We may also use a matching approach, comparing EV charging behavior in observably-similar households between C2 and T1, T2, T3, T4, T5, and T7.

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