Non-Experimental Estimates of the Effects of Managed EV Charging

Hunt Allcott Luming Chen*

September 26, 2024

1 Introduction

This report provides non-experimental estimates of the effects of managed EV charging. We combine the charge event data which covers a total of 21,370 vehicles with the load shape data for every 15-minute interval. We explore the basic charging patterns of electric vehicles. We then construct load counterfactuals under managed charging. Moreover, we exploit the timing variation of different vehicles adopting managed charging, and use this timing variation to identify the effect of managed charging on load shapes.

We first lay out a simple framework in Section 2. We then discuss the data and descriptive facts in Section 3. Section 4 discusses the algorithm we use to construct the counterfactual load shapes as well as the empirical strategy to identify the the effects of managed EV charging. Section 5 presents the empirical results.

2 Framework

2.1 Setup

Index consumers by i and time periods (e.g., hours or 15-minute intervals) by t. Consumer i's electricity consumption for electric vehicle (EV) charging in period t is q_{it}, in units of kilowatts (kW). Define $T \in \{1,0\}$ as the indicator for participation in the managed charging program. There are two potential outcomes: consumption under managed charging, and consumption under unmanaged charging, denoted q^1_{it} and q^0_{it}, respectively. Consumers pay retail price p_t, which may vary by period due to time-of-use pricing, as well as a fixed monthly charge F.

*Allcott: Stanford University, email: allcott@stanford.edu; Chen: Stanford University, email: luming.chen@stanford.edu.

The marginal social cost of charging i in t is c_{it}. This includes wholesale electricity acquisition, environmental externalities, and distribution transformer degradation costs. m_i is the utility from participating in managed charging. m could be positive or negative, e.g. related to the certainty of being charged and/or hassle costs of participating in the program. The value of having consumer i in managed charging is the sum of the social cost savings net of the participation disutility m_i. This value aggregated across consumers is

$$V = \sum_i \sum_t \left[\left(q^1_{it} - q^0_{it} \right) \cdot c_{it} - m_i. \right] \tag{1}$$

As in other causal inference problems, the fundamental challenge is that we don't observe both potential outcomes q^1_{it} and q^0_{it}, so V_i is unobserved. Moreover, the average treatment effect (ATE) is uninteresting here, because managed charging is designed to shift charging load from high-cost to low-cost periods, but not to reduce overall charging load.

Since we don't observe q^0_{it} for managed charging participants, we need a prediction $\hat{q}^0_{it}$. With that prediction, the estimated value is

$$\hat{V} = \sum_i \sum_t \left[\left(q^1_{it} - \hat{q}^0_{it} \right) \cdot c_{it} - m_i \right]. \tag{2}$$

The required unbiasedness condition for $\hat{V} = V$ is then

$$\sum_i \sum_t \left(q^0_{it} - \hat{q}^0_{it} \right) \cdot c_{it} = 0. \tag{3}$$

3 Data and Descriptive Facts

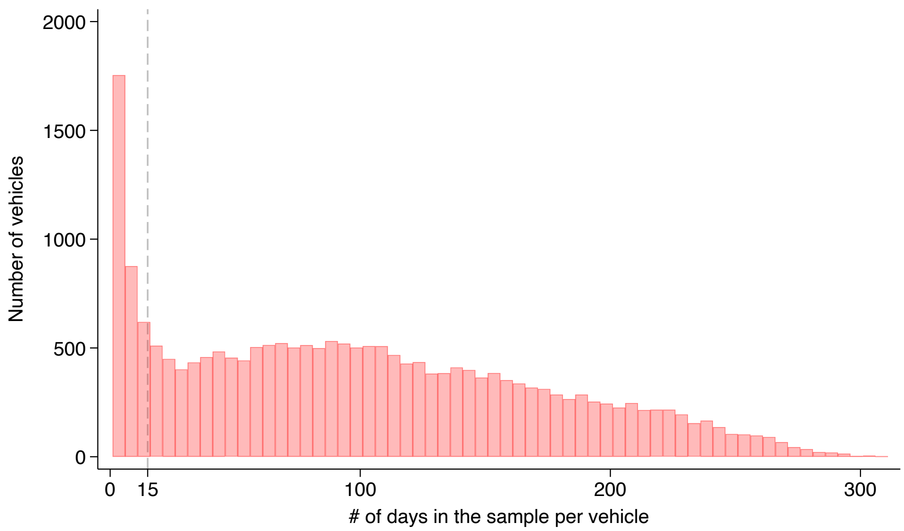
We first discuss the data variation that we exploit to identify the effect of managed charging (henceforth, MC). The main data set we use is "20230601-20240625 Charge Plug Park Events.csv." The observation is at the charging event level. There are in total of around 2.5 million charging events from around 21,000 vehicles. As the corresponding load shape data end on April 17, 2024, we keep the sample window from June 1, 2023 to April 15, 2024, a total of 320 days.

We define a "treatment" variable as whether a vehicle has adopted MC. We use the timing of the first managed charging event to measure the timing of adopting MC, which is constructed from the first charging event where "managed_charge_plan_id" is not missing for each vehicle.

3.1 Sample Section

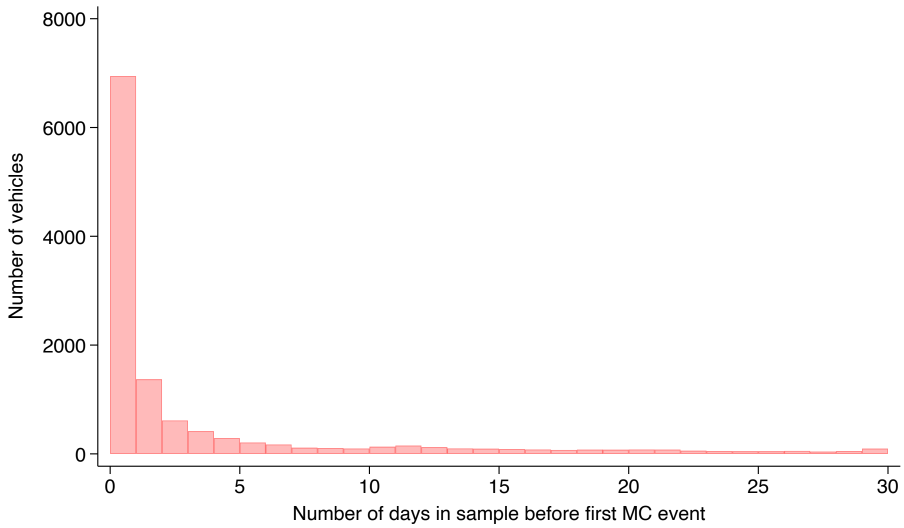
We first establish several descriptive facts to inform us about the sample selection. Figure 1 plots the number of days in the sample across vehicles. Among 21,201 vehicles in the sample, around 10% have fewer than 7 days in the sample, and 15% have fewer than 15 days. The mean and median days are 100 and 92, respectively. Our following empirical analysis would require vehicles to appear in the sample for a sufficiently long time. Without sacrificing too much of the cross-sectional variation, we keep vehicles with at least 15 days in the sample. Figure 2 further describes the the number of days in the sample before its first charging event across vehicles. 38% of the vehicles have already adopted MC from the very beginning, and around 50% of the vehicles have no more than 3 days in the sample before its first charging event. Therefore, we keep vehicles for at least 7 days before its first charging event to ensure a sufficient pre-treatment period.

Figure 1: Number of Days in Sample Per Vehicle



Notes: This figure plots the distribution of the number of days in the sample across vehicles.

Figure 2: Number of Days before First Managed Session Per Vehicle



Notes: This figure plots the distribution of the number of days in the sample before the first managed session across vehicles. We truncate the distribution and only keep vehicles with fewer than 30 days in the sample before the first managed session.

Table 1 summarizes the number of vehicles by different utilities. We keep utilities that have vehicles that are never managed and vehicles that have been managed and have at least 7 pre-managed days. Therefore, we keep utility numbers 2, 3, 4, 5, 7,8, 13, 58, and 129 in the sample.

Table 1: Number of Vehicles by Utility

Utility ID	Total number	Never managed	Ever managed	Always managed (0 pre-managed days)	Ever managed (7+ pre-managed days)
1	103	100	3	3	0
2	5,155	1,676	3,479	2,055	428
3	1,515	359	1,156	582	179
4	290	188	102	60	18
5	2,546	1,888	658	268	221
7	2,372	397	1,975	1,448	83
8	4,705	1,850	2,855	2,253	184
9	421	186	235	210	6
13	928	231	697	46	247
15	61	61	0	0	0
24	21	7	14	3	3
58	326	169	157	12	11
129	116	36	80	5	15
130	132	132	0	0	0
131	4	4	0	0	0
132	4	2	2	1	0

Notes: This table summarizes the number of vehicles by utilities. We first tabulate the number of vehicles that are never managed, ever managed, always managed (with zero day in the sample before the first managed session), ever managed but with more than seven days in the sample before the first managed session.

3.2 Charge at Home

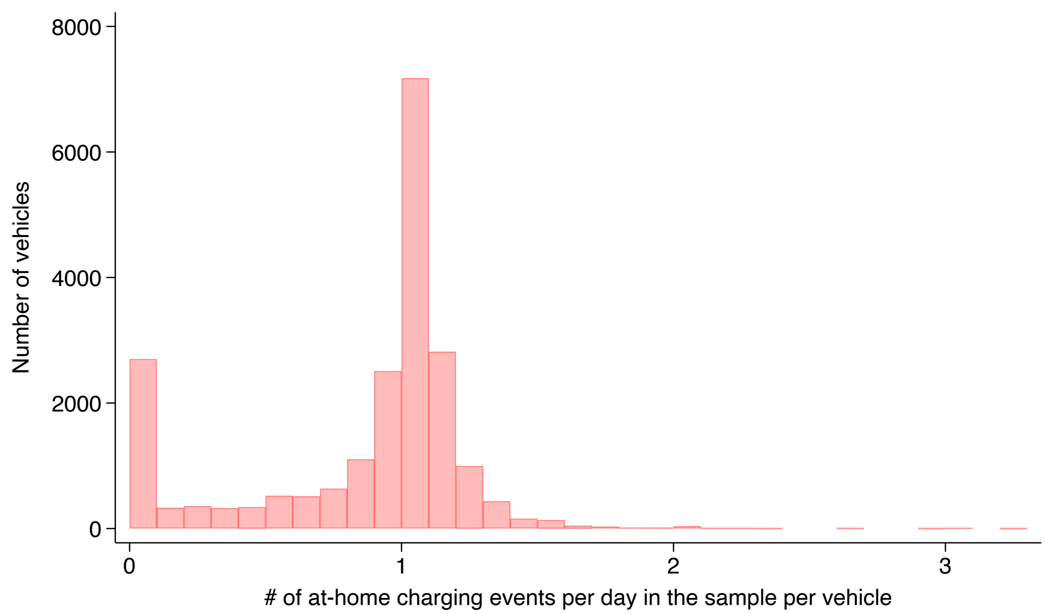
We further describe whether the vehicle charges at home. Table 2 cross-tabulate whether a charging event is under the managed charging and whether the charging is at home. Our sample covers roughly similar number of managed and unmanaged charging events. However, managed charging events happened almost exclusively at home, while 54% of the unmanaged charging events happen at home. Moreover, as shown in Figure 3, most of the vehicles have about 1 at-home charging event per day in the sample, while around 10% of the vehicles never charge at home.

Table 2: Plugged at Home and Managed Charging

	Managed charging events	Unmanaged charging events
At home	1,250,532	715,241
Away from home	238	598,622
Total charging events	1,250,770	1,313,863

Notes: This table summarizes the number of charging events by whether they are under the managed charging and whether the vehicles are plugged at home.

Figure 3: Number of At-home Charging Events Per Day

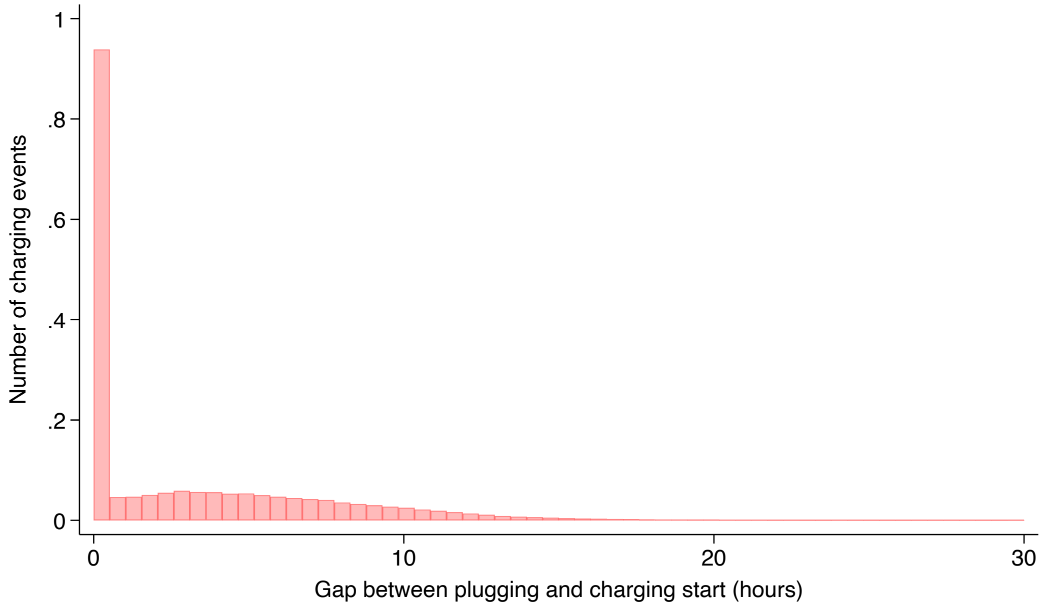


Notes: This figure plots the distribution of the number of at-home charging events per day in sample across vehicles.

3.3 Time from Plug to Charge

We describe the time from plug to charge for vehicles that have never adopted managed charging as in Figure 4. 50% of the charging events start immediately after the vehicle is plugged in, and 58% of the charging events start in less than 1 hour after the vehicle is plugged in. However, the distribution has a long right-tail, and the mean of the time gap is around 3.5 hours.

Figure 4: Histogram of Time from Plug to Charge for Vehicles Not Managed

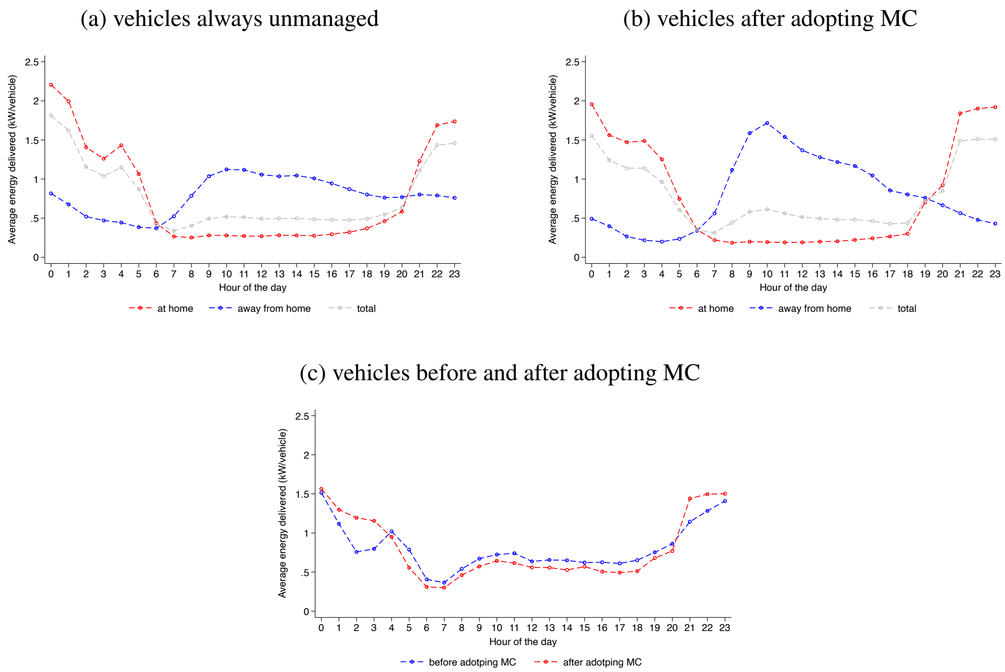


Notes: This figure plots the distribution of the time from plug to charge for vehicles that haven't adopted managed charging.

3.4 Load Shape

Figure 5 explores the load shape by vehicle groups. As shown in Panel (a), for vehicles that are always unmanaged, load from charge events at home accumulates after 17:00, peaks between 21:00 and 0:00, and gradually decreases to the trough at 7:00, when the load from charge events away from home begins to pick up. For vehicles after adopting MC, we observe more load after 21:00 but less load between 4:00 and 20:00.

Figure 5: Average Load Shape by Vehicle Groups



Notes: This figure plots the average load shape by the hour of the day for vehicles of different groups. Panel (a) plots the average load shape by the hour of the day for vehicles that are always unmanaged, by whether they are plugged at home or not. Panel (b) plots the average load shape by the hour of the day for vehicles that have adopted managed charging, by whether they are plugged at home or not. Panel (c) plots the average load shape by the hour of the day for vehicles before and after they adopt managed charging.

3.5 Charging Patterns

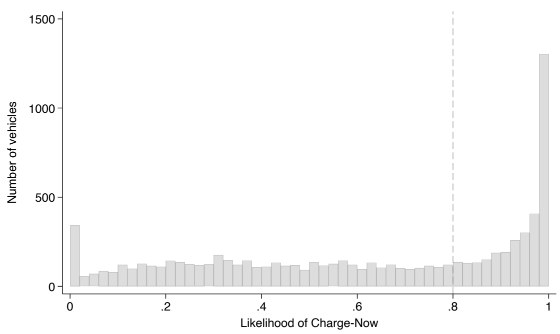
We explore the prevalence of three basic charging patterns among vehicles: charge-now, TOU, and charge-at-X. Charge-now pattern is defined as a vehicle starting the charging session within one hour after it is plugged in. TOU pattern is defined as a vehicle starting the charging session within one hour after the peak-rate end hour. Charge-at-X is defined as a vehicle starting the charging session at the vehicle-specific modal charging starting time X. For example, if vehicle A starts to charge at 19:00 most frequently, and vehicle B starts to charge at 21:00 most frequently, we define the charge-at-X as starting the charging session at 19:00 for vehicle A, and starting the charging session at 21:00 for vehicle B. Charge-at-X captures the habit or "default" behavior of the drivers.

We calculate the probability of following each of these three charging patterns among all the charging events for each vehicle, and then plot the distribution of the probability across vehicles in Figure 6. We restrict the sample to those vehicles that haven't adopted MC yet. As shown in Panel (a), charge-now seems to be a common charging pattern, which is as expected since 58% of the charging events start in less than 1 hour after the vehicle is plugged in as shown in Figure 4. Panel (c) suggests that the "default" behavior exists among the drivers, while Panel (b) suggests a low prevalence of the TOU pattern.

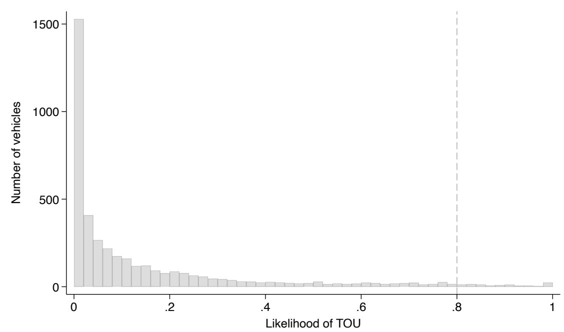
Moreover, we categorize vehicles into three types according to their charging patterns before they enter the MC program. If in more than 80% of the charging events, a vehicle follows the charge-now pattern, we define it as the "charge-now type." If instead in more than 80% of the charging events, a vehicle follows the charge-at-X pattern, we define it as the charge-at-X type." The rest of the vehicles are labeled as "others" since there is no apparent charging rule that they follow.

Figure 6: Charging Patterns for Vehicles Not Managed

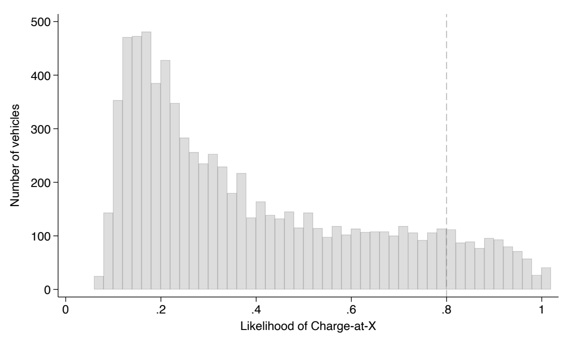
(a) charge-now



(b) TOU



(c) charge-at-X



Notes: This figure plots the distribution of the likelihood of three different charging patterns across vehicles. Panel (a) plots the distribution for the charge-now pattern. We define the charge-now pattern as starting charging less than 1 hour from the vehicle plugging in. We then calculate the likelihood of charging events following the charge-now pattern for each vehicle, and plot the distribution of the likelihood. Panel (b) plots the distribution for the TOU pattern. We define the TOU pattern as starting charging less than 1 hour from the peak rate ending hour. We then calculate the likelihood of charging events following the TOU pattern for each vehicle, and plot the distribution of the likelihood. Panel (c) plots the distribution for the charge-at-X pattern. We define the charge-at-X pattern as starting charging at the vehicle-specific modal charging starting time. We then calculate the likelihood of charging events following the charge-at-X pattern for each vehicle, and plot the distribution of the likelihood.

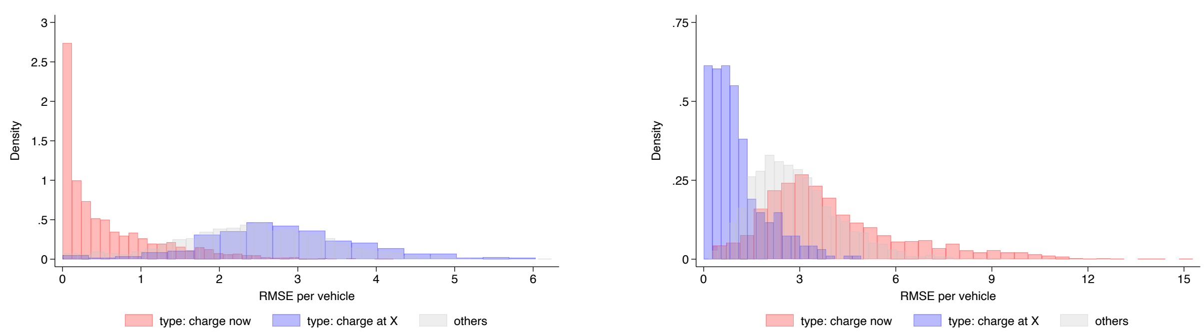
4 Empirical Strategy

4.1 Prediction Algorithm

We first examine how well the charge-now prediction and the charge-at-X prediction can fit the actual charging behavior. We define the actual load for vehicle i, charging event j, and hour t, as q_{ijt}, the charge-now prediction $\hat{q}_{ijt}^{charge-now}$, and the charge-at-X prediction as $\hat{q}_{ijt}^{charge-at}$. The vehicle-specific Root Mean Squared Error (RMSE) for the charge-now prediction is $RMSE_i = \sqrt{\frac{\sum_{jt}(q_{ijt} - \hat{q}_{ijt}^{charge-now})^2}{N_i}}$. The RMSE for the charge-at-X prediction is similarly defined. As shown in Figure 7, the RMSEs for the charge-now prediction are much smaller for the charge-now type, while the RMSEs for the charge-at-X prediction are much smaller for the charge-at-X type. The prediction errors are relatively large for the "others" type.

Figure 7: Validation of the Vehicle Charging Types

(a) charge-now (b) charge-at-X



Notes: This figure plots the Root Mean Square Error (RMSE) for the counterfactual predictions for vehicles of different types. Panel (a) plots the distribution of the RMSE between the actual load shape and the predicted load shape using the charge-now counterfactual for each vehicle, and the distributions are plotted separately for vehicles of the charge-now type, charge-at-X type, and others. Panel (b) plots the distribution of the RMSE between the actual load shape and the predicted load shape using the charge-at-X counterfactual for each vehicle, and the distributions are plotted separately for vehicles of the charge-now type, charge-at-X type, and others.

We construct a vehicle's counterfactual charging behavior combining its charge-now prediction, charge-at-X prediction, and a set of time fixed effects via a vehicle-specific linear regression. The regression model is as below.

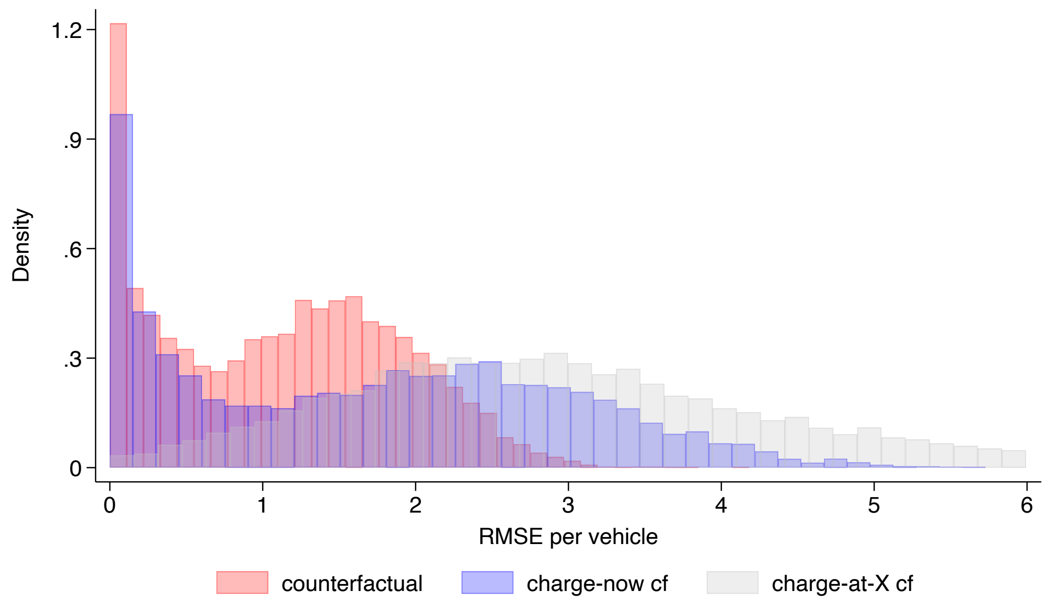
$$q_{ijt} = \beta_{i1}\hat{q}_{ijt}^{charge-now} + \beta_{i2}\hat{q}_{ijt}^{charge-at} + \xi_{it} + \varepsilon_{ijt}. \tag{4}$$

ξ_{it} denote the hour of the day and day of the week interacted fixed effects. We estimate the above equation vehicle by vehicle, so all the coefficient estimates are vehicle-specific. We then construct the counterfactual predictions as follows.

$$\hat{q}_{ijt} = \hat{\beta}_{i1}\hat{q}_{ijt}^{charge-now} + \hat{\beta}_{i2}\hat{q}_{ijt}^{charge-at} + \hat{\xi}_{it}. \tag{5}$$

A preliminary validation result is shown in Figure 8. The counterfactual predictions from Eqn. 5 yields much smaller RMSEs compared with the charge-now counterfactual and the charge-at-X counterfactual. We are currently working on alternative (better) ways to validate the counterfactual predictions.

Figure 8: Validation of Counterfactual Predictions



Notes: This figure plots the distribution of the RMSE for the counterfactual predictions $\hat{q}_{ijt}$, charge-now counterfactual, and charge-at-X counterfactual across vehicles that are unmanaged.

4.2 Empirical Model

We estimate the effects of adopting MC on the subsequent MC usages exploiting a difference-in-differences strategy. The empirical model is as follows.

$$q_{ijt}^{h} - \hat{q}_{ijt}^{h} = \sum_{d=-16, d\neq -1}^{30} \beta_d^h \mathbb{1}\{t - T_i = d\} + X_{it} + \xi_i + \xi_t + \varepsilon_{ijt}. \tag{6}$$

- i: vehicle ID; j: charging event ID; t: charging start date.
- q_{ijt}^{h}: the average energy delivered during hour h in the charging event j. $\hat{q}_{ijt}^{h}$: the counterfactual prediction of average energy delivered

- T_i: the date of MC adoption.

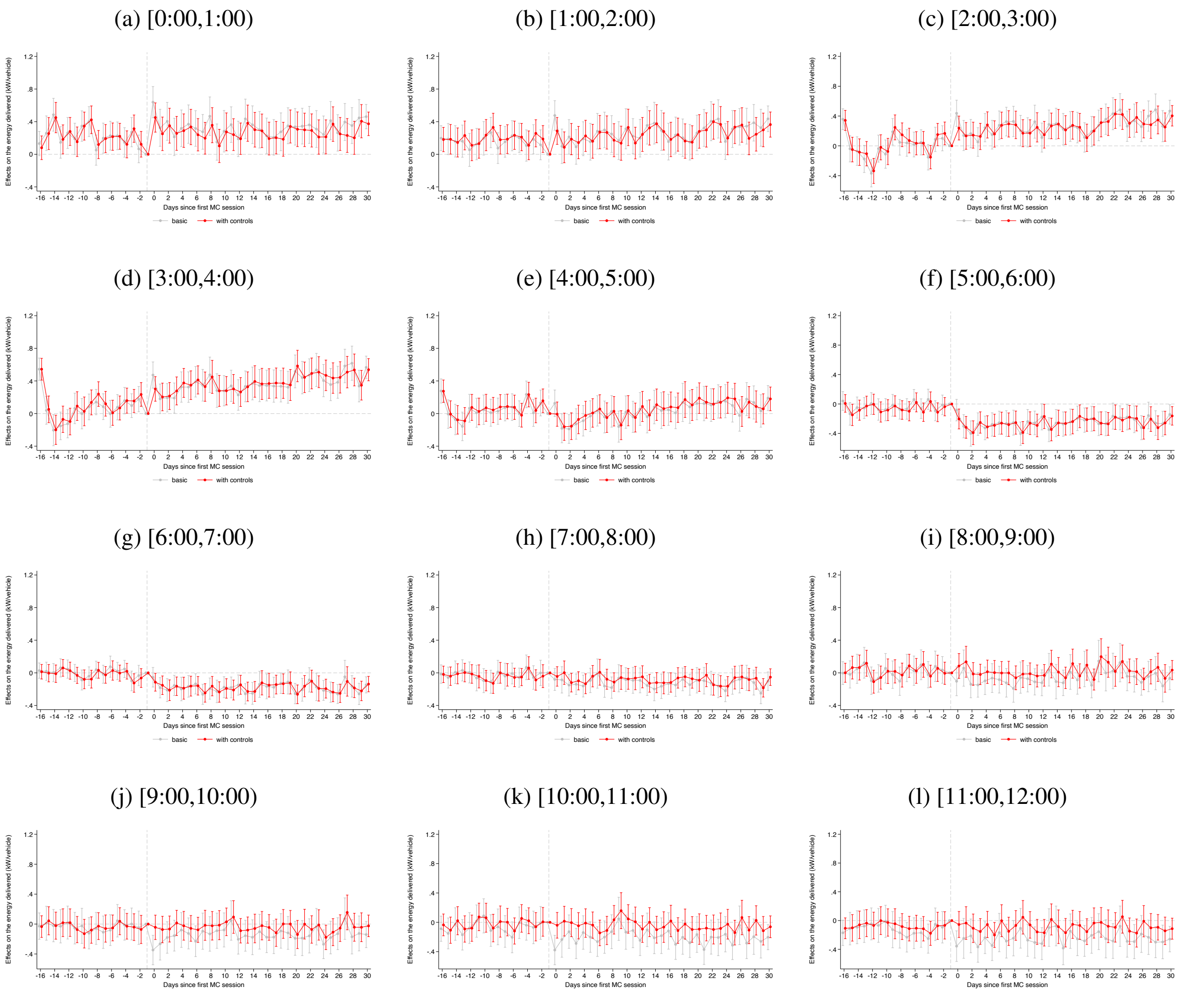
- ξ_i: vehicle fixed effects; ξ_t: date fixed effects; X_{it}: dummies for the plug-in hour, dummies for the TOU peak-end hour, dummies for total number of charge events on that day for the focal vehicle, and the SOC when charge event starts.

The empirical model follows the classical empirical design of difference-in-differences using two-way fixed effects. β_d^hs are a set of parameters of interest, which captures how the adoption of the MC program affects the average energy delivered. We keep charging events both plugged at home and away from home in this regression.

5 Effects of Managed Charging

We estimate the effects of MC on the energy delivered exploiting a difference-in-differences strategy. We plot the hour-by-hour event study in Figures 9 and 10.

Figure 9: The Effects of Managed Charging on Energy Delivered (AM)



(a) [0:00,1:00) (b) [1:00,2:00) (c) [2:00,3:00)

(d) [3:00,4:00) (e) [4:00,5:00) (f) [5:00,6:00)

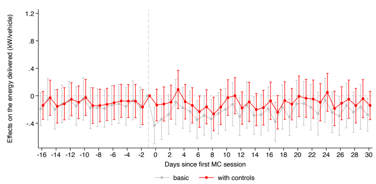
(g) [6:00,7:00) (h) [7:00,8:00) (i) [8:00,9:00)

(j) [9:00,10:00) (k) [10:00,11:00) (l) [11:00,12:00)

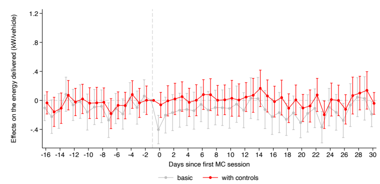
Notes: This figure plots the effects of MC on the average energy delivered. The coefficients in gray are estimated with vehicle fixed effects and date fixed effects. The coefficients in red are estimated with vehicle fixed effects, date fixed effects, plug-in hour fixed effects, TOU peak-end hour fixed effects, fixed effects for total number of charge events on that day for the focal vehicle, and the SOC when charge event starts.

Figure 10: The Effects of Managed Charging on Energy Delivered (PM)

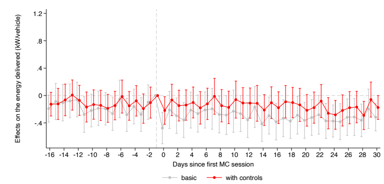
(a) [12:00,13:00)



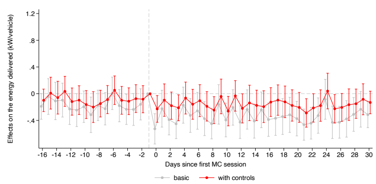
(b) [13:00,14:00)



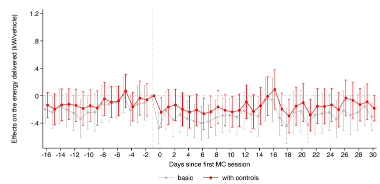
(c) [14:00,15:00)



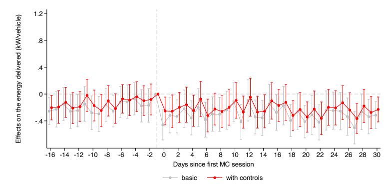
(d) [15:00,16:00)



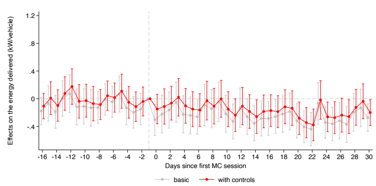
(e) [16:00,17:00)



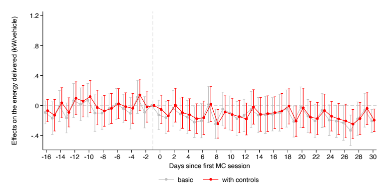
(f) [17:00,18:00)



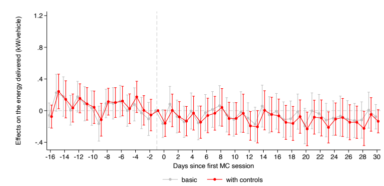
(g) [18:00,19:00)



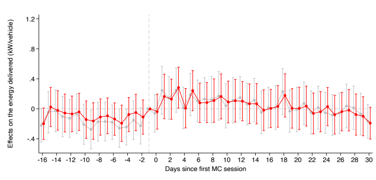
(h) [19:00,20:00)



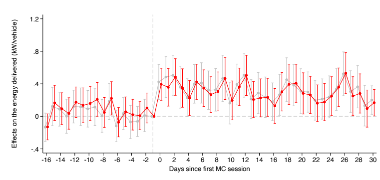
(i) [20:00,21:00)



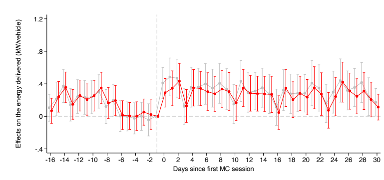
(j) [21:00,22:00)



(k) [22:00,23:00)



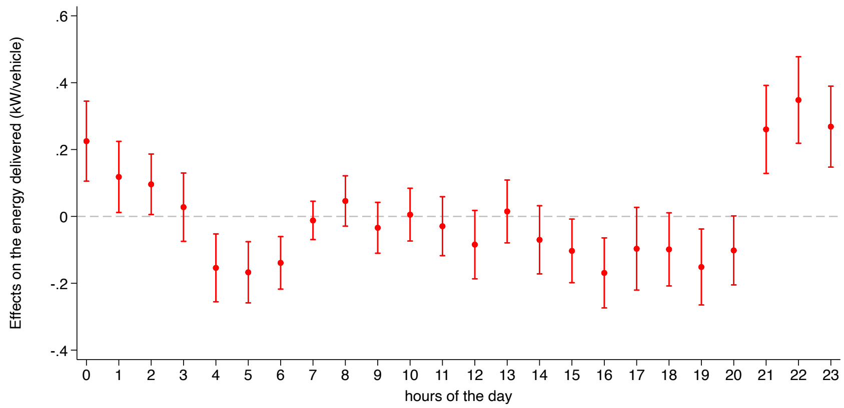
(l) [23:00,0:00)



Notes: This figure plots the effects of MC on the average energy delivered. The coefficients in gray are estimated with vehicle fixed effects and date fixed effects. The coefficients in red are estimated with vehicle fixed effects, date fixed effects, plug-in hour fixed effects, TOU peak-end hour fixed effects, fixed effects for total number of charge events on that day for the focal vehicle, and the SOC when charge event starts.

We plot summary of coefficient estimates by the hour of the day in Figure 11. Adopting MC increases the load after 21:00 and shifts the load away between 15:00 and 20:00. However, the load is also reduced between 4:00 and 6:00.

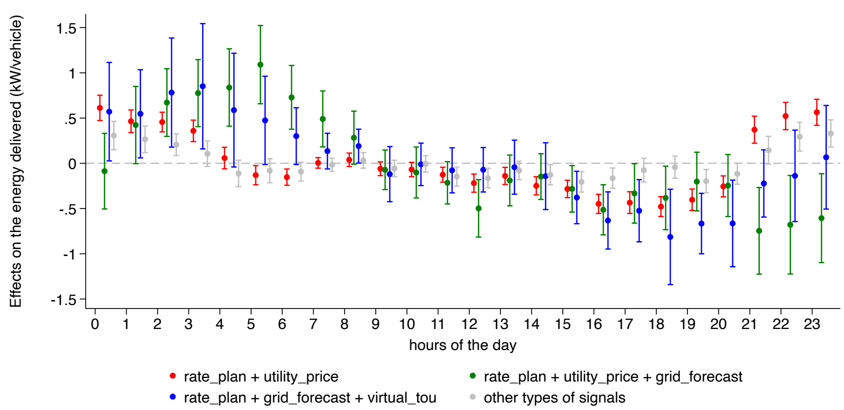
Figure 11: The Effects of Managed Charging on Energy Delivered



Notes: This figure plots the effects of MC on energy delivered.

We further investigate how the treatment effects differ across system signals. We categorize all the signals into four types: (1) "rate plan" + "utility price"; (2) "rate plan" + "utility price" + "grid forecast"; (3) "rate plan "+ "grid forecast" + "virtual tou"; (4) all other signal types. All signals contain "rate plan." The results are shown in Figure 12. When the system prioritizes minimizing utility costs (with "utility price"), the load is shifted from the late afternoon and early evening to after 9 pm. When the system prioritizes smoothing load (with "grid forecast"), the load is shifted from the late afternoon and evening to after midnight and early mornings.

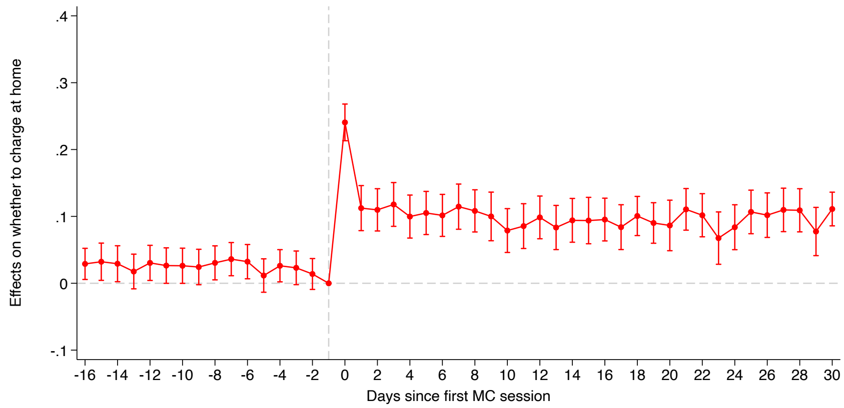
Figure 12: The Effects of Managed Charging on Energy Delivered by Signals



Notes: This figure plots the effects of MC on the energy delivered by signals.

We also find that vehicles are more likely to charge at home after they adopt MC, as shown in Figure 13.

Figure 13: Selection on Where to Charge



Notes: This figure plots the effects of MC on whether to charge at home.