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If You Build It, They May Not Come: Willingness to Participate in Managed EV Charging

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Abstract

Despite the importance of program participation for policy, treatment effects are often measured on self-selected samples. We study electric vehicle (EV) managed charging, intended to reduce electric grid strain by optimally allocating charging across EVs. Prior work finds large impacts of managed charging among households who volunteer for an RCT. In contrast, we test managed charging with an experiment including all EVs within a California utility. Enrollment is low even with high incentives, and we can reject even modest intent-to-treat effects on electricity consumption. Managed charging is less effective than previously thought, underscoring the value of population-wide experiments.

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1 Introduction

While randomized controlled trials are typically considered the "gold standard" approach for estimating causal impacts, they do not always provide the full picture necessary for conclusive policy evaluation. For many interventions, the most important parameter for a policymaker is the population-average intent to treat effect, which captures *both* program take-up *and* the effect of treatment on the treated. In settings where experimental subjects are themselves selected, the resulting treatment effect estimates are not guaranteed to reflect this parameter (Muralidharan and Niehaus (2017); Athey and Imbens (2017); Deaton and Cartwright (2018)). In such cases, researchers should strive to randomize the entire eligible population (or a randomly-selected sample thereof) in order to retrieve the policy-relevant ITT.[1]

We demonstrate the importance of measuring an ITT that reflects population-average program participation in the context of electric vehicle (EV) managed charging programs. Integrating large numbers of EVs into the energy system is a challenge that accompanies transportation decarbonization goals such as the eventual phase out of gasoline cars. Substantial policy efforts have been undertaken to decarbonize the electric grid, induce EV adoption, and build a sufficient network of charging stations. However, widespread transportation electrification will also place substantial strain on the electricity distribution system. EV adoption increases household electricity consumption by approximately 15% (Burlig et al. (2021)), and charging only a small number of EVs on a local distribution circuit at once can exceed transformer capacity, causing excess wear and tear and even failure of this critical infrastructure (Bailey et al. (2025a)). Engineering estimates suggest that the distribution system upgrade costs required to accommodate full vehicle electrification could reach hundreds of billions of dollars for the U.S. (Elmallah et al. (2022), Li and Jenn (2024)).

Faced with potentially dramatic increases in distribution system costs, regulators and distribution utility companies have three main options (Rapson and Shaffer (2025)): infrastructure investment, pricing, or load management. The most expensive option is to expand the distribution system to accommodate all patterns of EV charging. A less-costly alternative approach is managing distribution system congestion via electricity tariffs. However, prices that accurately reflect the costs EV charging imposes on the distribution system would require *location-specific* real-time pricing, because distribution constraints are time- and distribution circuit- varying. This is unlikely to be politically feasible, and we lack empirical evidence on the extent to which consumers would respond to this type of price signal. If

[1] Though this often occurs (e.g., Miguel and Kremer (2004); Schultz (2004); Olken (2007); Duflo et al. (2011); Muralidharan and Sundararaman (2011); Duflo et al. (2013); Fowlie et al. (2021); Greenstone et al. (2025), and others), it is far from universal.

pricing reflective of distribution level marginal cost is impractical, more blunt forms of pricing such as kilowatt service-level demand charges could be the most practical option (e.g., Turk et al. (2024), Ovaere and Vergouwen (2025)).

The final option is for the distribution utility to actively manage the usage of customers. We study one such option, which enrolled EV owners in a managed EV charging (MEC) program. In theory, managed charging can allow distribution utilities to directly control the timing of EV load, optimizing charging across vehicles within a circuit to avoid costly transformer capacity violations. Unlike tariff-based approaches where utilities can default customers into particular energy price plans (e.g., Fowlie et al. (2021)), MEC is necessarily opt-in: EV owners must grant the utility control over their vehicle's charging behavior. An electric utility is typically not even aware of when and if an EV is charging at any given location.[2] Most current EVs do collect a large amount of data on charging and performance, but these data are closely guarded by the vehicle manufacturers and are considered the confidential information of the vehicle owner. Residential managed EV charging, as a consequence, will likely require that customers provide vehicle data and surrender some degree of charging control to the utility. Therefore, measuring program participation, and how this is affected by incentives, is key to understanding the effectiveness of MEC.

In this paper, we partner with one of the most EV-dense utilities in the United States to run a randomized experiment. We randomly assign the vast majority of EV owners in this utility into one of a series of experimental arms.[3] Our main groups of interest are the control and treatment groups which receive varying financial incentives to join the MEC program. By randomly varying incentives for MEC participation and measuring opt-in rates, we estimate a population-wide "supply curve" for managed charging. We also use the experiment to estimate both ITT effects and LATEs of managed charging offers on electricity consumption and EV charging. In addition, we randomly offered some customers the option to participate in experimental electricity tariffs. Because all customers in our sample are already on time-of-use (TOU) pricing (i.e., they face lower prices in "off-peak" hours than in "peak" hours), we offered to steepen these TOU rates, raising the peak prices and lowering the off-peak prices, either for the entire home or for the EV alone. We can measure ITT effects and LATEs of these tariff changes on electricity use. This experiment therefore identifies a series of important parameters for regulators and electric utilities facing

[2]Using a unique dataset of household electricity consumption linked to DMV EV registration information, Burlig et al. (2021) find that the level and timing of residential charging in California did not match engineering-based estimates.

[3]Households were excluded from the experiment if they were not on one of the most popular electricity tariffs, but *all* customers on the main tariff classes were randomized. Households were *not* first recruited into the experiment and then randomized.

distribution network challenges from a growing fleet of EVs.

Our experiment produces three main findings. First, we estimate the supply curve of MEC by examining enrollment in the program at various incentive levels. We find low MEC participation at every incentive level. When offered no participation incentive, 1.0% of households enroll. When we raise the incentive to $40 per month – approximately 15% of the total monthly electricity bill – only 4.6% of households choose to enroll in the program. We demonstrate that these enrollment rates are far too low to alleviate the distribution capacity problem, even if the MEC program dramatically adjusted enrolled households' charging patterns. Second, households rarely activate the managed charging feature, exhibiting a strong preference for control over their own EV charging (or, equivalently, they are at best indifferent to ceding that control, even after having enrolled in the MEC program). That said, a within-household analysis of enrollees reveals differences in charging patterns between managed and unmanaged sessions suggesting that, if activated, the MEC would impact energy use. Third, as a result, both the ITT and LATEs of the managed charging program on the timing of EV charging are small. Moreover, at least in our setting, the social benefits are likely significantly smaller than the incentive payments required to induce enrollment. Finally, we find no impact of steepening households' TOU rates on electricity consumption.

These findings build on a growing literature of experimental work in energy economics.[4] We complement the existing literature by providing an estimate of the supply curve of managed EV charging at population scale. Two recent randomized controlled trials (Bailey et al. (2025b), La Nauze et al. (2024)) present LATEs of time-of-use pricing and other financial incentives that are designed to shift EV charging to time periods with low regional wholesale electricity costs. Another paper (Bailey et al. (2025a)) demonstrates how a utility-controlled MEC may be more effective than pricing at navigating local grid constraints. However, the design of these studies does not allow the authors to estimate the population-wide propensity to enroll in such programs, meaning that they cannot estimate ITT effects of offering an opt-in MEC program, and the LATEs they estimate likely come from a highly-selected sample.[5] Our results imply that, even if managed EV charging is effective for those who enroll, its overall impact could be limited by low enrollment. While San Mateo county may be considered an atypical customer-base, Metcalfe et al. (2026) find similarly low enrollment to an analogous service in a very different setting. This similarity helps to alleviate site selection concerns along the lines of Allcott (2015) and Ito et al. (2023).

Our antecedents in the literature emphasize the promise of pricing and managed charg-

[4] E.g. Garg et al. (2024); Blonz et al. (2025); Bernard et al. (2025).

[5] According to the description in Bailey et al. (2025a), subjects were recruited from a total population of 600,000 (includes non-EV owners) via social media and advertising. 202 participants enrolled in the experiment, and group randomization occurred thereafter.

ing treatments on populations that have agreed to participate in an experiment. Yet it is well understood, by them and others, that caution is warranted before extrapolating these impacts to the population. In our setting, randomizing the vast majority of EV owners allows us to demonstrate that take-up rates are incredibly low on average, even given relatively high-powered incentives, and we correspondingly find negligible ITT effects, which are important for understanding the overall impact of MEC programs.[6] These results underscore the importance of randomizing the policy-relevant population, rather than estimating treatment effects on a sample of willing experiment participants alone.

This paper proceeds as follows. Section 2 describes our experimental design, including the setting, treatment arms, and specifics of our MEC program. Section 3 describes the data we use in our analyses. Section 4 presents our results, and Section 5 concludes.

2 Experimental design

Context The experiment was implemented in collaboration with Peninsula Clean Energy (PCE). PCE is one of dozens of community choice aggregators (CCA) that have evolved to take a large market share of electricity retail service over the last decade.[7] PCE serves San Mateo county, a region on the San Francisco peninsula immediately south of San Francisco which has one of the highest EV adoption rates in the country. PCE has approximately 300,000 customers. It operates atop Pacific Gas & Electric (PG&E)'s distribution network, but sets its own prices.

Sampling frame All single-family households served by PCE that were known to own an EV at the time of randomization were enrolled in the experiment.[8] 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 the California

[6]The challenges of recruitment in our setting are reminiscent of those encountered by Fowlie et al. (2018) in the home energy retrofit setting.

[7]CCAs are locally governed, non-profit entities who operate in the retail service segment of the electricity industry. They are essentially resale entities that procure power at the wholesale level and resell it to customers located in their service territories. As community-governed organizations, CCAs have a large amount of discretion over the design of prices of electrical energy. In theory, CCAs therefore have more freedom to innovate with regards to tariff design and retail services. However, the charges for transmission, distribution, and other parts of electricity service are still collected by PG&E and set by the California Public Utilities Commission (CPUC). These latter components account for roughly 1/2 to 2/3 of electricity bills in California.

[8]For the purposes of this analysis, we exclude households with residential solar. The supply curve is similar, with enrollment peaking at 6.2% under a $40 per month incentive if we include these households (Appendix Figure B.1), but analyzing their energy consumption data is non-trivial because we are unable to observe total household energy consumption.

Department of Motor Vehicles. The final experimental sample consists of 12,174 households.

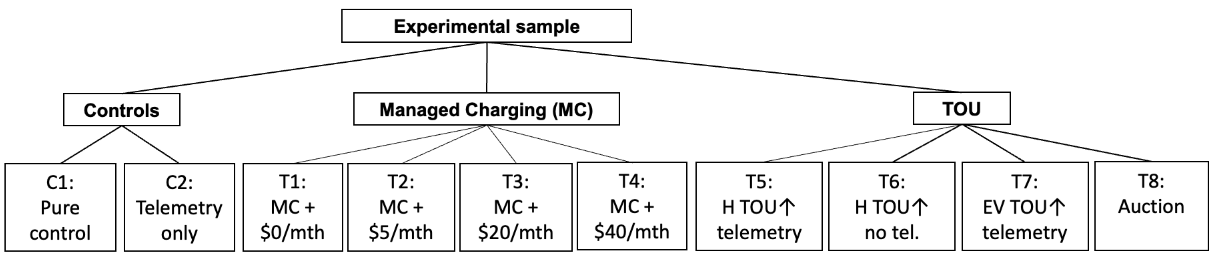
Managed charging Our main treatment of interest is a managed EV charging program, implemented through ev.energy, a smart EV charging platform. Customers in our managed charging arm received an email from PCE with an offer to enroll in managed charging, at incentive levels ranging from $0 per month to $40 per month (approximately 15% of the average monthly electricity bill). Customers were told that "[PCE's] new smart charging app will charge your electric car automatically during times of day with the cleanest and cheapest electricity, while making sure it's fully charged when you need it, and will tell you how much you're spending when you charge at home."

In order to join the program, customers downloaded the ev.energy app and completed the enrollment process, which included linking their EV to the app. Each time they plugged their EV into their home meter for charging, they had the option to allow ev.energy to "manage" that charging session, thereby allowing their charging to be scheduled via an algorithm. This algorithm prioritized a driver's "ready-by" time (i.e., a driver declares that the vehicle must be fully charged by 9 AM); the electricity price; high expected solar PV production (for households with installed solar); and carbon emissions, as predicted by WattTime. Importantly, this program imposed very low inconvenience costs on consumers.

Time-of-use pricing It may be possible to alleviate distribution network congestion using electricity pricing designed to disincentivize usage at peak periods. In order to have households internalize the externality they impose on the distribution network, these prices would need to be local and set in real time. This was not feasible to implement in our setting. Instead, even in the status quo, PCE's customers face time-of-use (TOU) electricity rates, where prices are lower during "off-peak" periods, and higher during "peak" periods. These prices and time periods are set well in advance. Our time-of-use treatments thus increased the wedge between peak and off-peak prices, raising the peak price by $0.05 per kWh and reducing the off-peak price by $0.05 per kWh. PCE was only able to offer these rate adjustments on an opt-in basis. As described below, we randomly assigned some customers to an offer of "steepened" TOU pricing for their whole house, and some customers to an offer of "steepened" TOU pricing only for their vehicle, as measured through telemetry data collected by the EV.energy app. There was no managed charging option available to these households.

Randomization We randomly assigned each household to one of 10 experimental arms, shown in Figure 1, and described below. The randomization was stratified by electricity rate (e.g., E-TOU-C or EV2A) and EV type (Tesla, PHEV, other BEV). All treatment cells with the exception of C1 were told they would be entered into a raffle to win a $500 cash prize if they enrolled, above any additional enrollment incentive from their specific treatment arm.

Figure 1: Experimental arms



Notes: This figure presents our experimental design, including all treatment arms.

- **C1, Pure control:** 156 hh. No intervention offer.
- **C2, Telemetry only:** 2339 hh. Invited to participate in a pilot program that monitored (but did not manage) their EV usage patterns via the ev.energy app. This is our main control group of interest.
- **T1, Managed charging, $0/mth:** 2269 hh. Invited to participate in the managed charging program with no financial incentive. Includes the same telemetry as in C2.
- **T2, Managed charging, $5/mth:** 1663 hh. Same as T1 but with $5/month participation incentive.
- **T3, Managed charging, $20/mth:** 968 hh. Same as T1 but with $20/month participation incentive.
- **T4, Managed charging, $40/mth:** 532 hh. Same as T1 but with $40/month participation incentive.
- **T5, House steep TOU + telemetry:** 1405 hh. Household load was exposed to a steepened time-of-use rate, plus the same telemetry offer as in C2.[9]
- **T6, House steep TOU + no telemetry:** 1233 hh. Household load was exposed to the same steepened time-of-use rate as in T5, but no monitoring of EV usage.

[9]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.

- **T7, EV-only steep TOU:** 1406 hh. 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.
- **T8, Auction:** 203 hh. These households were given the opportunity to enroll in managed charging via a BDM-style willingness-to-accept auction procedure. Ultimately, fewer than 20 households responded to the auction survey, so we exclude these households from our analysis.

3 Data

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 about 12 months before the experiment commenced and extends until the end of the experimental period. These data include unique household identifiers that allow for linkage to the other data sets.
2. **Utility customer data:** This utility-provided dataset is 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, T1-T5, and T7 who choose to enroll in telemetry. The data fields include: the time and duration of each charging instance, the location (home or away from home), type of charging (smart or unmanaged), and kWh delivered.

Experimental integrity Table 1 presents summary statistics in a balance table. All variables are measured over a consistent time period prior to the start of the experiment. On average, control-group households consume approximately 0.932 kWh per hour, rising to 0.964 at peak times. 66.3% of control-group households own a Tesla, with 15.2% owning a non-Tesla BEV. 43.1% of control households are on an EV-specific electricity tariff. Due to the stratification, the groups are balanced by design on their EV-type share and EV rate share, with only minor discrepancies (due to unequal group sizes). Reassuringly, we see no statistically or economically meaningful differences in overall electricity consumption or in peak electricity consumption, which were not used for stratification. Attrition is both low and similar across treatment arms (see Appendix Table B.1).

Table 1: Experimental balance

	Control		Managed Charging				TOU		
	-	Telemetry	0	5	20	40	Whole House + Telemetry	Whole House	EV Only
	C1	C2	T1	T2	T3	T4	T5	T6	T7
Mean (kWh)	0.952	0.932	0.916	0.960	0.917	0.900	0.914	0.943	0.929
	[0.817]	[0.647]	[0.654]	[0.928]	[0.666]	[0.557]	[0.669]	[0.779]	[0.660]
Mean Peak (kWh)	1.018	0.964	0.943	0.991	0.958	0.931	0.949	0.974	0.982
	[0.998]	[0.722]	[0.712]	[0.989]	[0.729]	[0.623]	[0.777]	[0.841]	[0.783]
% EV Households	77.6	81.5	81.3	81.8	79.3	83.5	82.4	78.3	80.9
% Tesla Households	63.5	66.3	65.7	65.2	63.4	66.4	66.0	64.0	64.7
% Non-Tesla BEV Households	14.1	15.2	15.6	16.6	15.9	17.1	16.4	14.4	16.2
% Households on EV Rate	39.7	43.1	42.0	40.0**	39.5*	42.9	42.6	43.1	41.5
Number of Households	156	2339	2269	1663	968	532	1405	1233	1406

Notes: This table presents experimental balance. We show means for all variables. For non-percentage variables, we show standard deviations in brackets. Stars indicate significance tests on the difference between each group and C2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Pre-analysis plan This study was pre-registered at the AEA RCT registry under Identification No. AEARCTR-0014013. We followed this plan closely, and the results described in Section 4 are as pre-specified unless otherwise noted. Deviations are minor and enumerated in Appendix D. Additional pre-specified results that do not appear in the main text or elsewhere in the Appendix can be found in Appendix C.

4 Analysis and results

We use our randomized trial to causally identify three key parameters. First, and perhaps most importantly, we measure the managed charging supply curve: how take-up of managed charging varies with incentive levels and examine how participation varies by observable characteristics, which is informative about the level of participation in managed charging that a utility can feasibly achieve and which customers can be induced to participate. Second, we measure the ITT effect of managed charging offers on electricity use. This describes the overall effect of the managed charging program, taking both the enrollment margin and any behavioral adjustments into account. Finally, we estimate the LATE of managed charging on electricity use, which provides policymakers with information about what managed charging is able to achieve conditional on enrollment.

Together, these measures describe enrollment in managed charging, treatment effects conditional on enrollment, and the overall impacts of offering a managed charging program on energy use. We also compare these managed charging ITTs and LATEs to those of our TOU tariff adjustments, in order to understand whether pricing reform may be a more effective approach to addressing distribution network congestion. Because enrollment in our setting is relatively low, and because enrolling in managed charging does not automatically mean that charge management is active, we also use a quasi-experimental estimator to measure how managed charging and unmanaged charging impact energy use for enrolled households, to better understand the extent to which activating managed charging changes load.

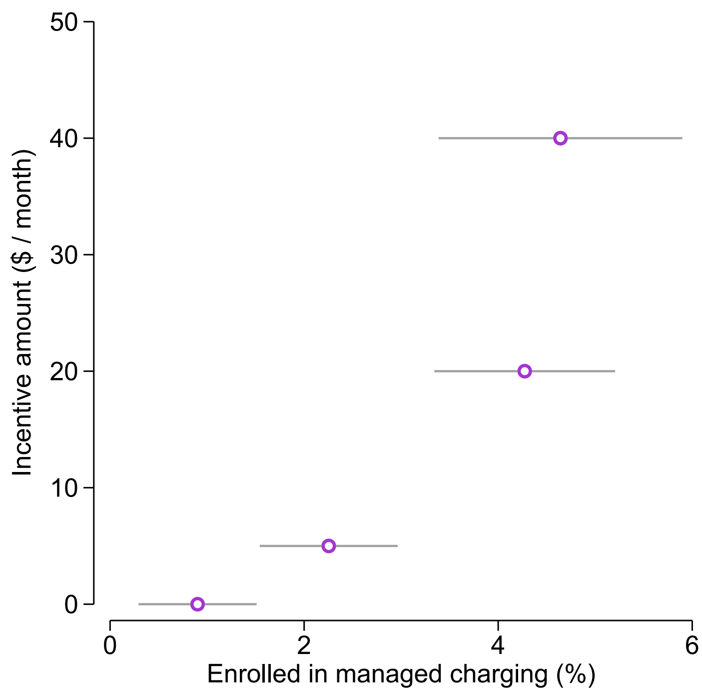
4.1 Managed charging enrollment

We begin by estimating the managed charging supply curve:

$$enrollment_i = \beta_0 + \sum_{k \in K} \beta_k T_{i,k} + \eta_s + \varepsilon_i, \tag{1}$$

where $enrollment_i$ is an indicator for whether household i enrolled in managed charging, $T_{i,k}$ are indicators for being randomized into treatment group $k \in K = \{C2, T1, T2, T3, T4, T5, T6, T7\}$.[10] Control group C2 is the omitted category. η_s are strata fixed effects, and ε_i is an error term. Figure 2 presents the results which, together, comprise a MEC supply curve. The vertical axis shows the monthly incentive offered to customers and the horizontal axis plots the share of customers who participate in managed charging at each incentive level, and its corresponding confidence interval.[11]

Figure 2: Managed charging supply curve



Notes: This figure plots managed charging enrollment by incentive level. We estimate this using Equation (1), which includes regressors for each treatment arm and strata fixed effects. We plot 95% confidence intervals, derived from heteroskedasticity-robust standard errors, in light gray.

Our first key finding is that enrollment in managed charging is incredibly low. When no incentive is offered, less than 2% of invited customers enrolled. At \$5 per month, participation increased, but to just over 2%. At \$20 per month, the enrollment rate was just over 4%. Finally, a \$40 per month incentive leads to enrollment of only 4.6%.[12] In addition, we

[10] 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.

[11] Appendix Table 2 presents a regression analogue, showing enrollment relative to control group C2.

[12] While enrollment is low, disenrollment is essentially non-existent. Only five households actively disen-

find that enrollment in managed charging with a \$0 monthly incentive is approximately 50% lower than enrollment in telemetry alone; at \$5 per month, enrollment in managed charging and telemetry are indistinguishable (Appendix Table 2). This suggests that low enrollment in managed charging is not only due to privacy concerns about sharing vehicle data with the utility. Broadly, our estimates imply that deploying widespread managed charging will be very difficult for utilities since they cannot default consumers into these schemes and must rely on voluntary participation.

It is important to emphasize that enrollment in this program is low despite several features that might have been expected to increase participation. First, the managed charging program we study was not particularly burdensome to customers. Customers had the ability to opt for "unmanaged" charging every time they connected at home, and indeed many did so. About 20% of the customers in the managed charging treatment group never actually undertook a managed charging session, but nevertheless received their monthly incentive. All their home charging was unmanaged, effectively overriding the remote management options. This suggests that customers may strongly dislike sharing their data with the utility, even if they can avoid having the utility actively control their charging behavior. Second, PCE's service territory is in San Mateo County, California, home to a large concentration of early EV adopters. This group of customers may be even more likely than the average American to enroll in a managed charging program, because they are particularly enthusiastic about EVs, and, in the heart of Silicon Valley, are likely more willing to engage with apps. Finally, PCE is a relatively well-regarded utility, meaning that consumers may be less averse to sharing their data voluntarily than they would be with a standard IOU with lower favorability metrics. However, these customers are also likely to be relatively wealthy, so they may be less attentive to utility incentives than the median Californian or American household. Though we do not know the extent to which these findings would generalize in other settings, the unwillingness of our population to engage in managed charging is striking.

rolled from the managed charging group (see Appendix Table B.2).

Table 2: Selection into enrollment

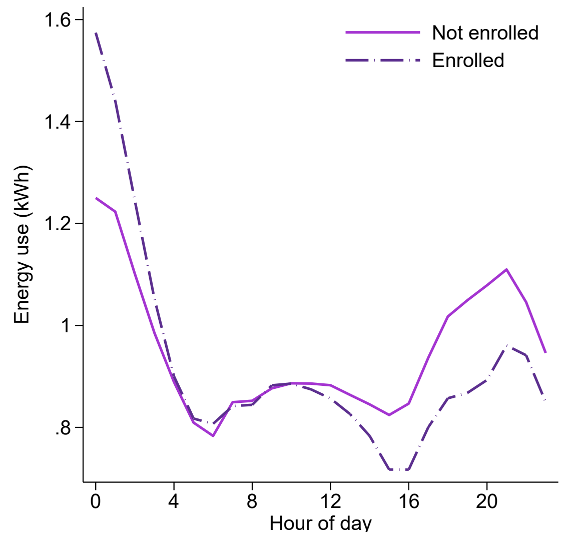
		Control	Managed Charging				TOU		
			0	5	20	40	Whole House + Telemetry	Whole House	EV Only
	Enrolled	C2	T1	T2	T3	T4	T5	T6	T7
Mean (kWh)	Yes	1.116	0.916	1.020	1.049	0.792	0.967	1.012	0.934
	No	0.958	0.954	0.998	0.959	0.949	0.946	0.973	0.955
	Difference	0.157	-0.038	0.022	0.090	-0.157	0.021	0.039	-0.021
		(0.097)	(0.148)	(0.162)	(0.110)	(0.126)	(0.129)	(0.121)	(0.093)
Mean Peak (kWh)	Yes	0.807	0.749	0.940	0.855	0.675	0.720	0.752	0.749
	No	0.938	0.928	0.969	0.948	0.941	0.925	0.950	0.957
	Difference	-0.131	-0.179	-0.029	-0.093	-0.266**	-0.206	-0.199	-0.208*
		(0.102)	(0.151)	(0.166)	(0.113)	(0.134)	(0.138)	(0.121)	(0.108)
% PHEV Households	Yes	10.2	23.8	24.3	12.2	20.0	18.5	22.2	28.0
	No	18.7	19.0	18.1	21.0	16.7	17.6	21.8	19.0
	Difference (pp)	-8.5	4.9	6.2	-8.8	3.3	0.9	0.4	9.0
		(5.6)	(8.6)	(6.4)	(6.5)	(7.7)	(7.4)	(6.3)	(5.7)
% Tesla Households	Yes	61.2	52.4	54.1	53.7	56.0	70.4	62.2	50.0
	No	66.3	65.6	65.2	63.5	66.0	65.7	63.8	64.8
	Difference (pp)	-5.1	-13.2	-11.1	-9.9	-10.0	4.6	-1.5	-14.8**
		(6.8)	(10.4)	(7.9)	(7.7)	(9.8)	(9.2)	(7.3)	(6.9)
% Non-Tesla BEV Households	Yes	28.6	23.8	21.6	34.1	24.0	11.1	15.6	22.0
	No	15.0	15.5	16.7	15.5	17.3	16.7	14.4	16.2
	Difference (pp)	13.6***	8.3	4.9	18.6***	6.7	-5.6	1.1	5.8
		(5.2)	(7.9)	(6.2)	(5.9)	(7.8)	(7.2)	(5.4)	(5.3)
% Households on EV Rate	Yes	73.5	71.4	67.6	85.4	68.0	70.4	82.2	72.0
	No	42.4	41.8	39.0	37.5	41.9	42.3	42.1	40.2
	Difference (pp)	31.0***	29.6***	28.6***	47.9***	26.1**	28.1***	40.1***	31.8***
		(7.1)	(10.8)	(8.1)	(7.7)	(10.1)	(9.6)	(7.5)	(7.1)
Number of Households	Yes	49	21	37	41	25	27	45	50
	No	2180	2121	1543	877	480	1302	1101	1275

Notes: Means reported as levels; Differences are Yes–No. Stars: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors appear in parentheses on the next line within each Difference cell. Enrollment rule: Telemetry (C2, T1–T4, T7); TOU enrollment (T5, T6). Time Period for Balance Check: Mar 1st 2023- April 30th 2023

Selection into enrollment We investigate the pre-treatment characteristics of the households who did versus did not enroll in managed charging in Table 2. We do not observe large differences between enrollees and non-enrollees in overall or peak energy consumption. We do see some evidence that enrollees are more likely to have non-Tesla BEVs, and less likely to own Teslas (though these estimates are not statistically different from zero), perhaps because it is more straightforward to set a bespoke charging schedule in a Tesla than in other EV models, so Tesla-owning households may be less interested in turning to an outside form of charging management. We also find that households who are already on an EV electricity rate are much more likely to enroll in the managed charging program. These households also appear more likely to enroll in the TOU pricing plans, suggesting that they may be more attentive consumers overall.

Figure 3 shows the hourly electricity consumption patterns during the pre-treatment period of households who, when offered an opportunity to join the managed charging program, do enroll (dark dashed purple) vs. do not enroll (solid light purple). The enrolling households have higher energy usage during the midnight to 4 AM period, and lower consumption during the afternoon/evening peak period. This suggests that experimental variation is important in estimating treatment effects of managed charging on electricity consumption, as enrolled vs. non-enrolled households have fundamentally different usage patterns.

Figure 3: Selection into managed charging enrollment by hourly usage pattern



Notes: This figure plots differences in pre-treatment electricity consumption across hours of the day for households who do vs. do not enroll in managed charging during the experiment. We plot average consumption in each hour for eventually-enrolled households (dark dashed purple) and never-enrolled households (solid light purple), restricting the sample to only households who eventually received managed charging offers.

4.2 Effects of treatments on energy use

Overall ITT effects Next, we estimate the effects of managed charging and steepened TOU pricing on energy consumption. We begin by estimating overall ITT effects, pooling all managed charging offer groups (T1, T2, T3, T4), whole-house TOU offer groups (T5, T6), and EV-only TOU groups (T7). Although groups T1-T4 received different incentives to enroll, their treatments are otherwise identical. For these three groups of treatment we estimate the following:

$$\begin{aligned} kWh_{it} = {} & \beta_1 \mathbf{1}[\text{Managed charging offer}]_{it} \\ & + \beta_2 \mathbf{1}[\text{Whole-house TOU offer}]_{it} \\ & + \beta_3 \mathbf{1}[\text{EV-only TOU offer}]_{it} + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it} \end{aligned} \tag{2}$$

where kWh_{it} is household i's electricity consumption in hour-of-sample t, $\mathbf{1}[\text{Managed charging offer}]_{it}$, $\mathbf{1}[\text{Whole-house TOU offer}]_{it}$, and $\mathbf{1}[\text{EV-only TOU offer}]_{it}$ are indicators for each household's treatment cell, 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.

Table 3: Treatment effects on energy use

	(1) kWh
Managed charging offer	-0.00381
	(0.00449)
Whole-house TOU offer	-0.0105
	(0.00645)
EV-only TOU offer	-0.00842
	(0.00806)
Control mean	0.929
Observations	170,020,188

Notes: This table presents the overall intent-to-treat effects of managed charging offers, whole-house TOU offers, and EV-only TOU offers on electricity consumption. The dependent variable is the kWh of electricity consumption per hour. The unit of analysis is the household-by-hour observation. All regressions include household, week-of-sample, and hour-of-day fixed effects. Standard errors, in parentheses, are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents the results. We find no impact of managed charging on overall electricity consumption. Our point estimate of -0.00381 kWh per hour implies a 0.4% reduction in consumption relative to the control mean, and we can reject a decline greater than 1.4%. This is perhaps unsurprising, given that managed charging enrollment is very low. Even in the $40 per month incentive group, however, we estimate an intent-to-treat effect of an 0.6% reduction in energy use, and can reject a reduction greater than 2.8%. We can therefore strongly rule out that offering managed charging had an economically meaningful impact on overall energy use. We measure similarly precise null results for our TOU arms, with whole-house TOU offers reducing overall energy consumption by 1.1% of the control mean and EV-only TOU offers reducing consumption by 0.9% of the control mean. In this setting, neither opt-in managed charging nor opt-in TOU steepening meaningfully impacts consumers' aggregate energy usage.

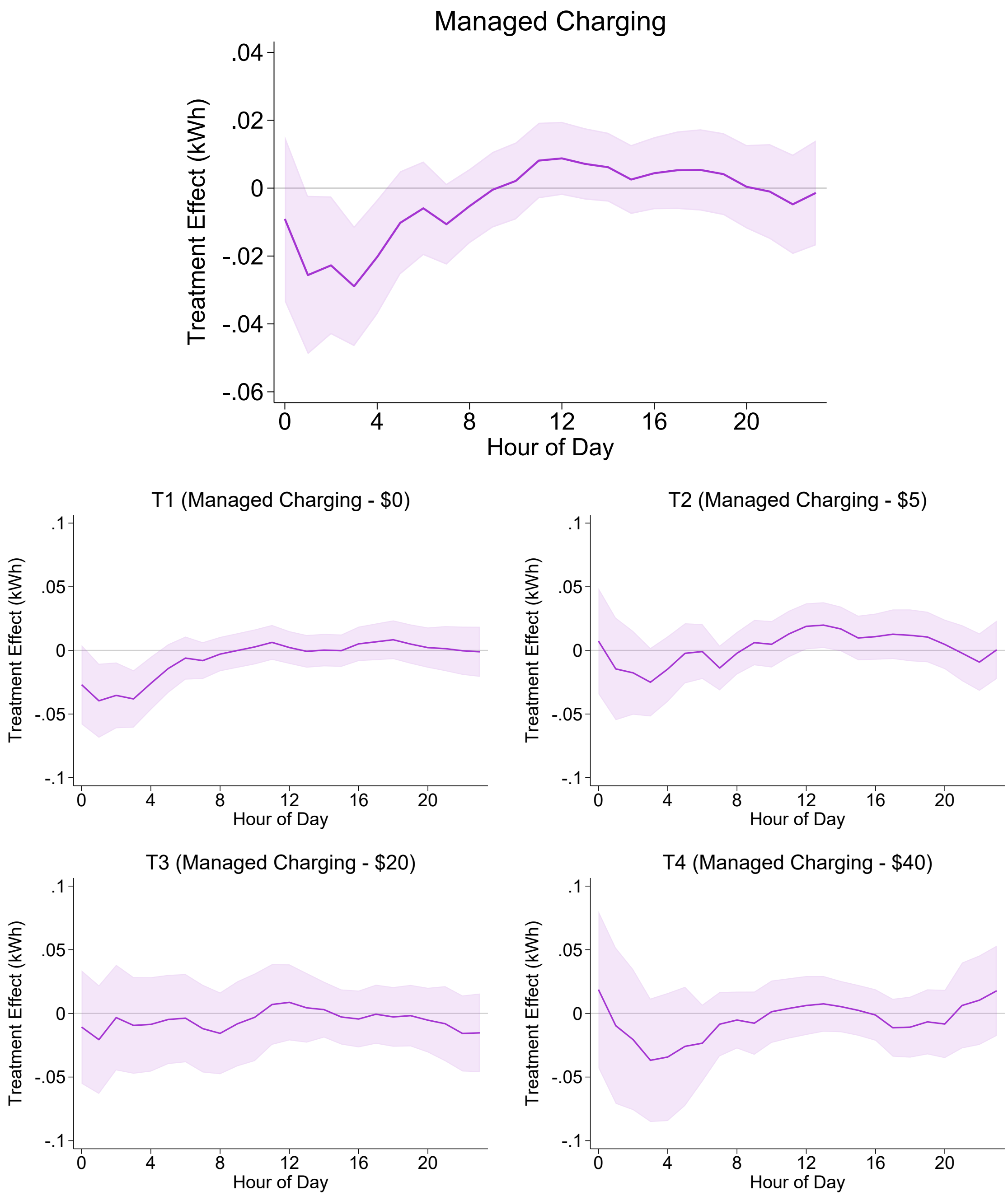
Hourly ITT effects It need not be the case that managed charging or TOU price steepening impacts *overall* electricity usage. These programs may instead be simply shifting load throughout the day rather than adjusting its level. To test for this, we now estimate hour-of-day specific treatment effects:

$$
\begin{aligned}
kWh_{ith} = \sum_{h=0}^{23} &\beta_1^h \mathbf{1}[\text{Managed charging offer}]_{it} \times 1[hour = h] \\
&+ \beta_2^h \mathbf{1}[\text{Whole-house TOU offer}]_{it} \times 1[hour = h] \\
&+ \beta_3^h \mathbf{1}[\text{EV-only TOU offer}]_{it} \times 1[hour = h] + \alpha_i + \delta_m + \delta_d + \delta_h + \varepsilon_{it},
\end{aligned} \tag{3}
$$

where $\mathbf{1}[\text{Managed charging offer}]_{it} \times 1[hour = h]$, $\mathbf{1}[\text{Whole-house TOU offer}]_{it} \times 1[hour = h]$, and $\mathbf{1}[\text{EV-only TOU offer}]_{it} \times 1[hour = h]$ are treatment indicators (defined as in Equation (2 above), now interacted with dummy variables for each hour of the day, and all else remains the same.

Figure 4 presents the hour-of-day specific ITT effects for the managed charging group. In the top panel, we present the pooled effect of managed charging. In the bottom four panels, we show the effects for each incentive level separately. As with the aggregate regressions, we are able to reject economically meaningful ITT effects of managed charging. We see some evidence that energy consumption is lower in the 0 to 4 AM period, these effects are extremely small – we can reject changes larger than -0.05 kWh per hour in the pooled regression. These results suggest that though managed charging may be doing something to shift load, it is only detectable in our setting because of our large sample size.

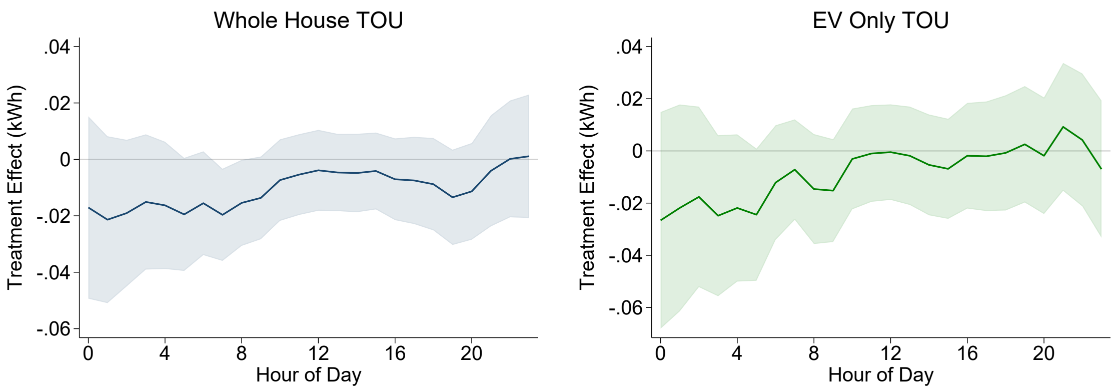
Figure 4: Managed charging: ITT estimates by time of day



Notes: This figure reports hour-of-day–specific intent-to-treat (ITT) estimates of the effects of treatment offers on electricity consumption. For each hour $h \in 0, \ldots, 23$, we estimate a separate regression of hourly kWh on indicators for treatment assignment. In the top panel, we estimate one effect (per hour of day) for assignment to managed charging, whole-house TOU, and EV-only TOU offers, restricting the sample to observations with hour-of-day equal to h. In the bottom four panels, we estimate separate treatment effects for each managed charging incentive level, including controls for the other treatment arms. The dependent variable is the mean kWh of electricity consumption in that hour. The unit of analysis is the household-by-hour observation. Standard errors are clustered at the household level, and we report 95% confidence intervals in the shaded area.

Figure 5 presents the corresponding hourly ITT effects for the TOU price steepening. We find no evidence of load shifting as a result of the TOU price steepening, and can again rule out economically meaningful impacts. Given that only 72 households (3%) chose to enroll in whole-house TOU steepening, and only 50 households (4%) chose to enroll in EV-only TOU steepening, these null ITT effects are unsurprising.

Figure 5: TOU steepening: ITT estimates by time of day

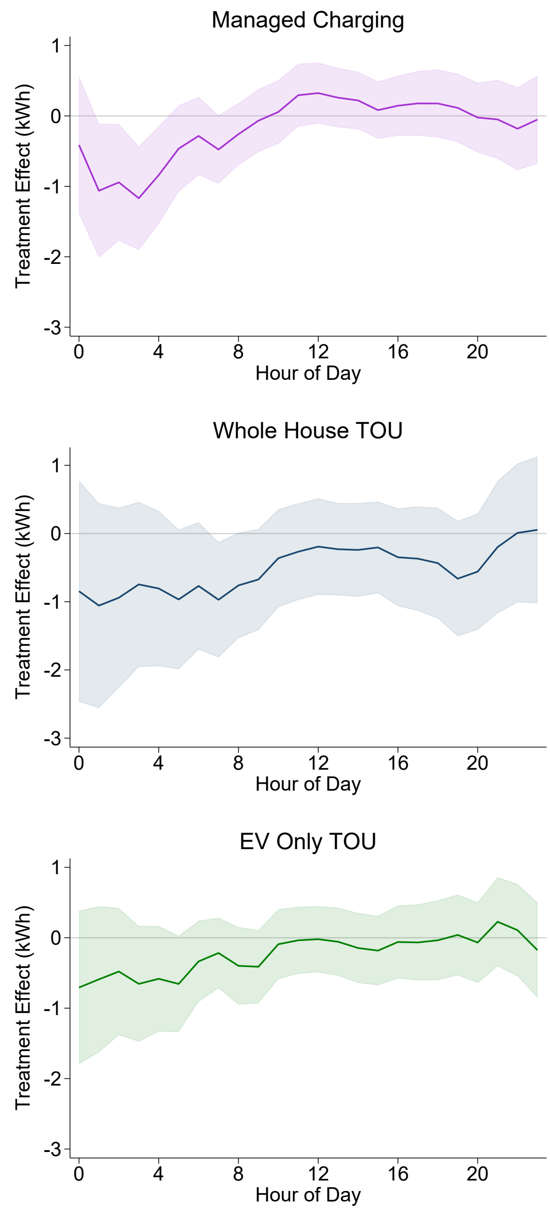


Notes: This figure reports hour-of-day–specific intent-to-treat (ITT) estimates of the effects of treatment offers on electricity consumption. For each hour $h \in 0, \ldots, 23$, we estimate a separate regression of hourly kWh on indicators for treatment assignment. In the left panel, we present the effect of whole-house TOU offers, and in the right panel, we present the effect of EV-only TOU offers, in both cases restricting the sample to observations with hour-of-day equal to h. We include controls for the managed charging treatment. The dependent variable is the mean kWh of electricity consumption in that hour. The unit of analysis is the household-by-hour observation. Standard errors are clustered at the household level, and we report 95% confidence intervals in the shaded area.

LATEs Finally, we estimate Local Average Treatment Effects (LATEs): for compliers, what is the causal impact of enrollment in managed charging or TOU steepening? We present hour-of-day specific estimates, using a variant of Equation (3) where we instrument for take-up with offers. Figure 6 presents the results.[13] We find some evidence that managed charging reduced electricity usage between midnight and 4AM, but see limited evidence of impact in other hours. We do not detect any statistically significant impacts of TOU steepening on hourly electricity consumption, in keeping with prior evidence that consumers are inattentive to price levels beyond the existence of peak vs. off-peak periods (e.g. Jessoe et al. (2014) and Gillan (2017)). Our LATE estimates are much noisier than our ITT effects, which is unsurprising, given the very small number of households that enrolled in these opt-in programs.

[13]Appendix Table B.4 presents the results in tabular form.

Figure 6: LATE estimates by time of day



Notes: This figure reports hour-of-day–specific local average treatment effect (LATE) estimates of the effects of treatment offers on electricity consumption. For each hour $h \in 0, \ldots, 23$, we estimate a separate regression of hourly kWh on indicators for treatment enrollment, instrumented with randomized offers. In the top panel, we present the effect of managed charging, in the middle panel, we present the effect of whole-house TOU steepening, and in the bottom panel, we present the effect of EV-only TOU steepening, in all cases restricting the sample to observations with hour-of-day equal to h. The dependent variable is the mean kWh of electricity consumption in that hour. The unit of analysis is the household-by-hour observation. Standard errors are clustered at the household level, and we report 95% confidence intervals in the shaded area.

Discussion We document three key facts. First, enrollment in managed charging is very low, even with high incentive levels. This is particularly remarkable because the managed charging intervention is relatively light-touch: households could in principle earn money without activating their charge management whatsoever, suggesting that they may experience meaningful disutility simply from sharing their vehicle data with PCE. Second, largely as a result of low enrollment, we estimate precise null ITT effects of the managed charging program: in its current form, PCE's managed charging offers do not impact overall electricity use. Third, our LATEs reveal that, among compliers, managed charging reduces electricity usage during the early morning hours, but has no effects at other times of day. Taken together, these results suggest that managed charging is unlikely to materially alleviate distribution constraints under voluntary participation at observed enrollment rates.

4.3 Effects of managed charging among enrolled households

The fact that we estimate null ITT effects of managed charging is unsurprising, given our low take-up rates. However, even with low enrollment rates, one might expect the point estimates for the hourly treatment impacts of managed charging to show substantial load shifting. This is not the case. Moreover, even though enrollment was low, among enrolled customers, 80% activated managed charging at least once. This raises the possibility that the managed charging algorithm is simply not shifting customers' load. Because even enrolled customers needed to activate managed charging, we cannot rule this out using our experimental variation alone. Instead, we use a within-customer design among enrolled customers to compare electricity use during managed charging sessions, unmanaged charging sessions, and no charging to document the relationship between managed charging sessions and energy use.[14]

We use our telemetry data from ev.energy to estimate the relationship between (managed) charging and energy use:

$$kWh_{ith} = \theta_1 \mathbf{1}[\text{Managed charging}]_{ith} + \theta_2 \mathbf{1}[\text{Unmanaged charging}]_{ith} + \alpha_{ih} + \delta_{th} + \varepsilon_{ith} \quad (4)$$

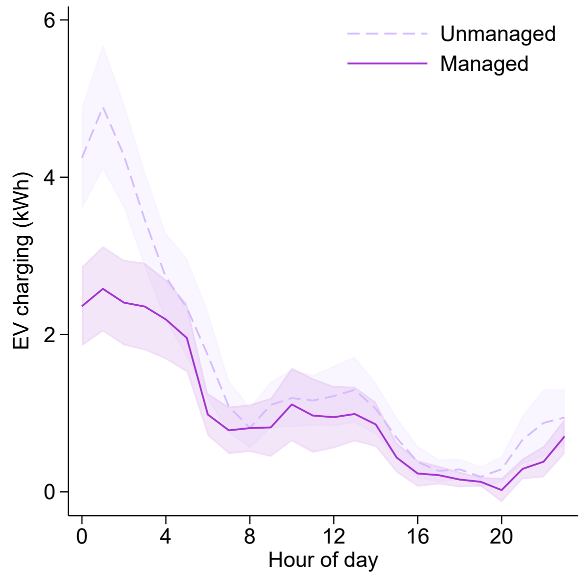
where kWh_{ith} is kWh of electricity consumed by household i on date t in hour-of-day h, as measured using the AMI data; $\mathbf{1}[\text{Managed charging}]_{ith}$ and $\mathbf{1}[\text{Unmanaged charging}]_{ith}$ are indicators, coming from the ev.energy data, on whether (managed) charging was taking place during this hour (with no charging as the omitted category), α_{ih} are household-by-hour-of-day fixed effects, δ_{th} are date-of-sample-by-hour-of-day fixed effects, and ε_{ith} is an error term clustered at the household level. All observations are from the experimental period,

[14]This analysis was not pre-specified.

as we have no telemetry data prior to the experiment. θ_1 and θ_2 represent the difference in electricity use between managed charging sessions, unmanaged charging sessions, and periods of no charging. In order for these coefficients to have a causal interpretation, the decision to activate managed charging needs to be as good as random. While this specification is quite saturated, threats to identification (e.g., a household activates managed charging only on days when they are unlikely to drive later on) may persist, so we interpret these results with some caution. Nevertheless, even interpreted descriptively, they provide some insight.

Figure 7 presents the results. Compared with no charging, unmanaged sessions increase electricity usage substantially during the 0 to 4AM time period, more modestly between 8AM and 3PM, even more modestly between 4PM and 8PM, and again increase usage from 8PM onwards. Managed charging sessions also increase usage compared to no charging from midnight to 4PM, but the increases – particularly between midnight and 4AM – are much more muted. Moreover, managed charging eliminates electricity consumption above non-charging periods during the 4PM to 9PM peak hours. These early-morning results align with our LATEs, which showed that managed charging enrollment leads to reductions in electricity usage during the midnight to 4AM hours. We do not see LATE effects from 4 to 9PM, though unmanaged charging use during this time is also relatively low. Overall, we see these results as providing evidence that the ev.energy managed charging program *is* able to adjust vehicle charging behavior when active.

Figure 7: Association between (managed) charging and electricity use



Notes: This figure plots the relationship between energy consumption and managed charging (solid purple) and unmanaged charging (dashed purple), compared to no charging. We estimate the relationship using Equation (4). Standard errors are clustered by household, and we present 95% confidence intervals in the shaded area.

4.4 How much managed charging is needed?

While the low participation rates documented here appear discouraging, it may be the case that even low levels of managed charging could be sufficient to alleviate most distribution constraints. In this section, we examine this possibility. We use public transformer capacity data from PG&E for San Mateo County in a simple simulation exercise to quantify how much managed charging participation would be required to avoid distribution capacity violations.[15] Households are connected to the electric grid via a distribution feeder, which is downstream of (at least) one distribution transformer. The capacity of these transformers determines how much concurrent electricity demand can be supported by the circuit, and upgrading transformer capacity is very expensive. Repeatedly exceeding a transformer's capacity reduces its longevity and can lead to failure (NREL, 2024). We observe 173 distribution feeders that lie within the Peninsula Clean Energy territory. The median feeder serves approximately 1,330 customers and has a minimum capacity of 910 kW.

To simulate how managed charging could impact transformer capacity violations, let C_i be

[15]These data are hosted on PG&E's Grid Resource Integration Portal https://grip.pge.com.

the amount of spare capacity on transformer i, measured in kilowatts (kw). $C_i = \overline{C}_i - kw_i^{max}$, where $\overline{C}_i$ is total transformer capacity and kw_i^{max} is the highest load we observe in the data (i.e., under business-as-usual operations). Suppose that each level two (L2) EV charger draws kw_{L2} of load. The maximum number of new L2 chargers that can charge concurrently on the circuit without a capacity violation is thus $\overline{N_i^{L2}} = C_i/kw_{L2}$.[16] Define N_i^{L2} as the number of incremental L2 chargers on the circuit. If $N_i^{L2} > \overline{N_i^{L2}}$, the distribution utility will need to control $N_i^{L2} - \overline{N_i^{L2}}$ chargers via managed charging to avoid capacity violations.

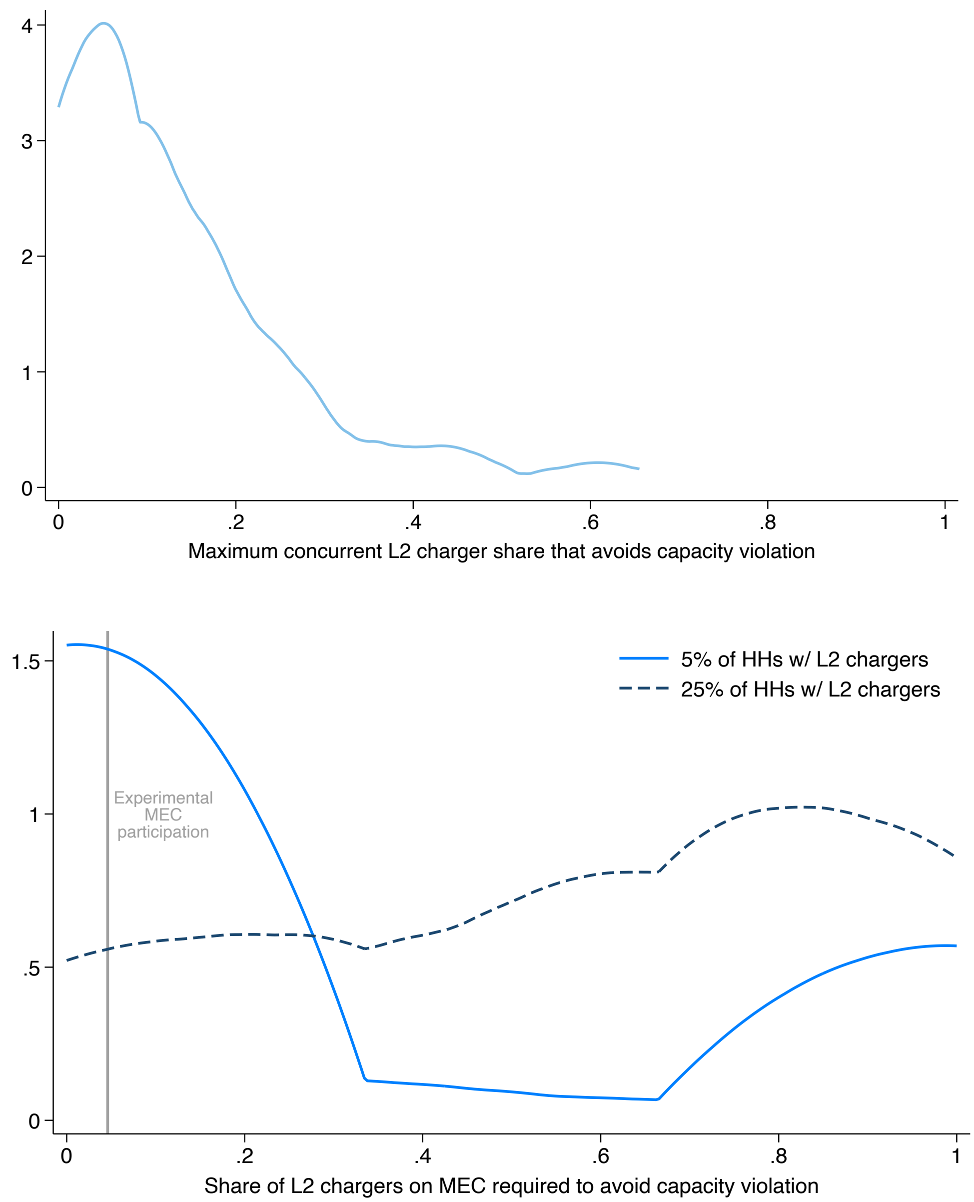
Our simulation reflects optimistic assumptions about the effectiveness of MEC. We assume that all managed charging households are "active" (i.e., no opting out) and that the algorithm is optimized to avoid capacity violations on the observed transformers in their most congested hour. While we do not explicitly simulate load shifting, the hourly profiles of feeder load indicate that there is capacity for MEC algorithms to do so. Moreover, we assume that $kw_{L2} = 7$, which is the modal load for residential L2 chargers (U.S. Department of Energy, n.d.), and that there are no other sources of incremental load.

Figure 8 summarizes the simulation results. The top panel plots the density of the maximum share of households that could newly acquire an L2 EV charger and charge it in the most congested hour without violating the transformer capacity constraint, absent any managed charging. Each observation is one feeder in our data. Feeders with high maximum concurrent L2 charger shares have substantial excess capacity available, whereas feeders with low maximum concurrent L2 charger shares are already at or close to the capacity constraint in the status quo. We find that the vast majority of the transformers in San Mateo County can accommodate new L2 EV chargers in only 30 percent of households or fewer, absent any managed charging.

Our calculation likely overstates the headroom of these feeders for at least two reasons. First, the PG&E data we utilize aggregates both capacity and load from all feeder segments within a given feeder into an aggregate feeder value. We are therefore not able to measure the capability of individual feeder segments, some of which may reach their capacity limits before the aggregate feeder to which they belong does. Second, we consider only the thermal MW capacity limits and not voltage limits on the feeders in our data. Third, the simulation errs towards conservative estimates of incremental load (from which we exclude all incremental household uses beyond L2 EV chargers) and load-shifting capacity (which we implicitly assume is unconstrained).

[16] In the status quo, many of these circuits are already home to L2 chargers. Because we do not observe L2 chargers at the circuit level, these are included in our baseline. Our simulation, therefore, estimates the number of *additional* L2 chargers that could be added without causing capacity violations.

Figure 8: Substantial MEC participation is required (simulation)



Notes: The top figure plots the density of maximum share of L2 EV chargers that can charge concurrently without violating transformer capacity capacity. Below are the densities of fraction of households required on MEC assuming L2 EV chargers are present in 5% (solid blue) and 25% (dashed navy) of households. The vertical gray line plots the share of households who participated in MEC under the highest incentive in our experiment. The simulation assumes that MEC is active in all MEC households, that the algorithm is optimized to avoid transformer capacity violations.

In the lower panel, the solid blue and dashed navy lines reflect assumptions that 5% and 25% of households newly adopt L2 chargers, respectively. The plotted lines measure how many of these households would need to be on a (fully-optimized) managed charging program to avoid capacity constraints.[17] The results show an intuitive pattern. On circuits with a low (5 percent) L2 share, transformer capacity violations can be avoided by enrolling a relatively small fraction of L2 households – under 30 percent in most cases – in managed charging. When the L2 market share is higher (25 percent), however, we only avoid capacity violations by enrolling the majority of L2 households in managed charging. Our experiment revealed that only 4.6% of EV households were willing to enroll in managed charging when given a $40 per month incentive (vertical gray line). Per our simulations, this enrollment rate would be sufficient to avoid transformer capacity violations in 56% of feeders under low EV penetration growth, but only 9% of feeders under high EV penetration growth.

In order for (perfectly-optimized) managed charging to solve the distribution capacity challenge in the vast majority of feeders, enrollment would need to be substantially higher than we estimate in our experiment.[18] While it is possible that other utilities would be more successful in recruiting customers into managed charging, note that (i) Metcalfe et al. (2026) finds similar managed charging enrollment rates in a very different setting; and (ii) the managed charging program we study in our experiment was much less onerous for consumers than the program we impose in our simulation. Therefore, distribution utility companies and regulators may wish to consider alternate ways to manage transformer capacity constraints under increasing EV and L2 charger penetration.

There are several alternatives to voluntary MEC.[19] One option is to require all high-capacity home EV chargers to be registered with the distribution utility and automatically enrolled in an MEC program whose algorithm is optimized for transformer capacity constraints. While this would require additional regulation, it has the benefit of overcoming the difficulty, uncertainty and cost involved in voluntary MEC program enrollment. Distribution utilities could also create incentives that reduce peak household demand. These may include household service capacity subscriptions that cap peak demand at the subscribed level, which households could increase with a higher grid connection charge. Utilities could also offer households compensation for enrolling in demand response programs that directly control temperature set points on heating and cooling and/or throttle the use of other high-load appliances. Location-specific dynamic electricity pricing is also an option. Households on congested transformers could face critical peak events or real-time pricing. Success of

[17]For context, suppose that 80 percent of EV owners charge at home (U.S. Department of Energy (2024)) and 80 percent of those households use L2 chargers (Chen et al. (2025) and JD Power (2026)). Under these assumptions, it requires 8% and 40% EV fleet share to achieve 5% and 25% incremental L2 charger adoption, respectively.

[18]Note that this is the case despite the fact that our calculation makes several assumptions that bias downward the fraction of managed charging necessary to avoid constraint violations, including a generous definition of feeder capacity and of the efficacy of managed charging amongst those enrolled.

[19]For a more comprehensive review of these options, see Rapson and Shaffer (2025).

such programs would require utilities to possess timely and spatially granular information, and for households to either automate their responses to unpredictable price increases or to overcome their own information and attention barriers to responding to high-frequency electricity price changes.

5 Conclusion

In this paper, we investigate the potential for remote management of EV charging load as a tool for managing system-level and local grid and supply constraints. To do so, we implement a randomized controlled trial among the population of EV-owning households served by Peninsula Clean Energy, a community choice aggregator in San Mateo, California, located on the San Francisco Peninsula. Randomly selected households are invited to participate in various pricing and management interventions. We offer a range of incentives to customers in different treatment cells to enroll in remote charging management.

Previous research has identified the limits of dynamic pricing for managing local constraints, given the lack of pricing granularity at the distribution level. The main alternative to pricing is direct management of consumption. While the technological capabilities for remote management are readily available, it is not clear how enthusiastic customers will be to its adoption.

Our paper highlights just how difficult it may be to achieve widespread adoption of remote charging. Enrollment rates in managed charging were below 7%, even for customers offered an incentive of $40/month (15% of the monthly electricity bill) to participate. Even among enrollees, active participation in managed charging was sporadic, at best. Therefore, while there is evidence that load was shifted in the manner intended during instances of actively managed EVs charging sessions, these sessions were infrequent and did not produce meaningful overall shifts in consumption even in the local average treatment effects.

From a policy perspective, these results highlight the need for careful program design and a thoughtful matching of incentives to the desired performance. One-time or even monthly payments for managed charging are weak mechanisms for achieving desired results when customers have the option to bypass settings while at home. However, more rigid compliance requirements for those who participate will likely further lower the rate of enrollment.

Given the high likelihood that distribution-system congestion will become a binding constraint on household electrification, our findings and the broader literature suggest several constructive avenues for regulators. At present, mandating participation in managed charging programs is difficult because distribution utilities generally cannot observe which customers own EVs or high-capacity chargers. If registration of such equipment were required, however, it would be feasible to make managed charging the default option – an approach that, in other settings, has substantially increased enrollment. Regulators might also consider tariff designs that more directly address distribution system externalities, such as demand charges or capacity subscription services (see Turk et al. (2024)). In any case, traditional residential rate structures – whether flat or coarse TOU designs – are poorly suited to meeting these emerging challenges.

Finally, our study also underscores an important distinction between population ITTs – such as the effect of offering managed charging to all EV owners on energy consumption – and treatment effects estimated on selected subsamples. In the managed charging context, these approaches yield contrasting results that imply very different levels of reliance on such programs to mitigate electricity system congestion. Although some of the divergence may reflect features specific to our setting, it is nonetheless informative to observe the demand for these programs in one of the most EV-dense regions of the U.S.

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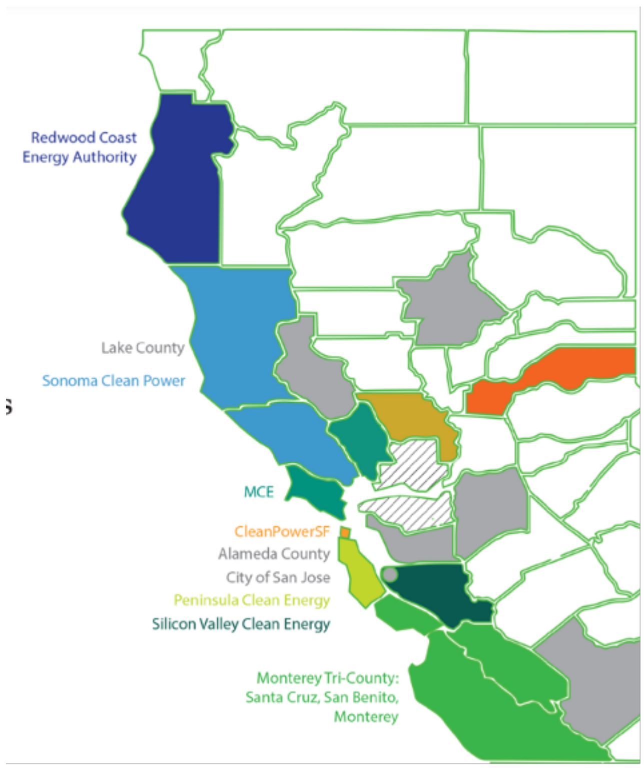
If you build it, they may not come: Willingness to participate in managed EV charging
Online appendix

Fiona Burlig, James Bushnell, and David Rapson

Contents

A Additional experiment details

Figure A.1: Peninsula Clean Energy Territory



Notes: This figure plots the location of the community choice aggregators within the San Francisco Bay Area. Peninsula Clean Energy's service territory, where our experiment takes place, is in lime green.

B Appendix tables and figures

B.1 Experimental integrity

Table B.1: Attrition

	(1)
Control (C1)	-0.014
	(0.016)
Managed charging offer ($0)	-0.001
	(0.006)
Managed charging offer ($5)	0.004
	(0.007)
Managed charging offer ($20)	-0.007
	(0.008)
Managed charging offer ($40)	-0.010
	(0.010)
Whole-house TOU offer + Telemetry	0.005
	(0.008)
Whole-house TOU offer	-0.001
	(0.008)
EV-only TOU offer	0.009
	(0.008)
Control mean	0.048
Observations	11,163

Notes: This table reports estimates from a linear probability model regressing an indicator for attrition – defined to be equal to 1 if the household has no AMI observation in the final 2 weeks of the 6 months after treatments began. We estimate this regression at the household level. The omitted category (and thus the control mean) is for the telemetry-only control group (C2). All specifications include strata fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Telemetry enrollments and dropouts by treatment arm

Group	Total customers	Telemetry	Dropouts
Control (C1)	156	–	–
Control + Telemetry (C2)	2,339	49	2
Managed charging offer ($0)	2,269	21	2
Managed charging offer ($5)	1,663	37	2
Managed charging offer ($20)	968	41	1
Managed charging offer ($40)	532	25	0
Whole-house TOU offer + Telemetry	1,405	41	2
Whole-house TOU offer	1,233	–	–
EV-only TOU offer	1,406	50	0

Notes: This table reports the count of households in enrollment and disenrollment of telemetry among each of our experimental groups. Dropping out from telemetry disenrolls a household from managed charging or EV-only TOU, if applicable.

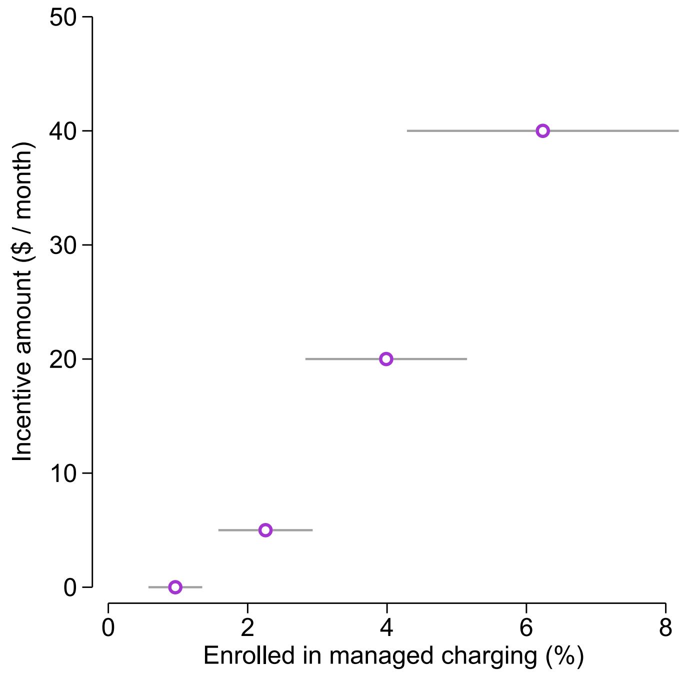
B.2 Managed charging supply curve

Table B.3: Program participation by treatment arm

	(1)
	Take-up
Managed charging offer ($0)	-0.0114***
	(0.00357)
Managed charging offer ($5)	0.00203
	(0.00466)
Managed charging offer ($20)	0.0223***
	(0.00707)
Managed charging offer ($40)	0.0260***
	(0.00959)
Whole-house TOU offer + Telemetry	-0.00313
	(0.00460)
Whole-house TOU offer	0.0155**
	(0.00605)
EV-only TOU offer	-0.0199***
	(0.00305)
Control Mean	0.021
Observations	11,815

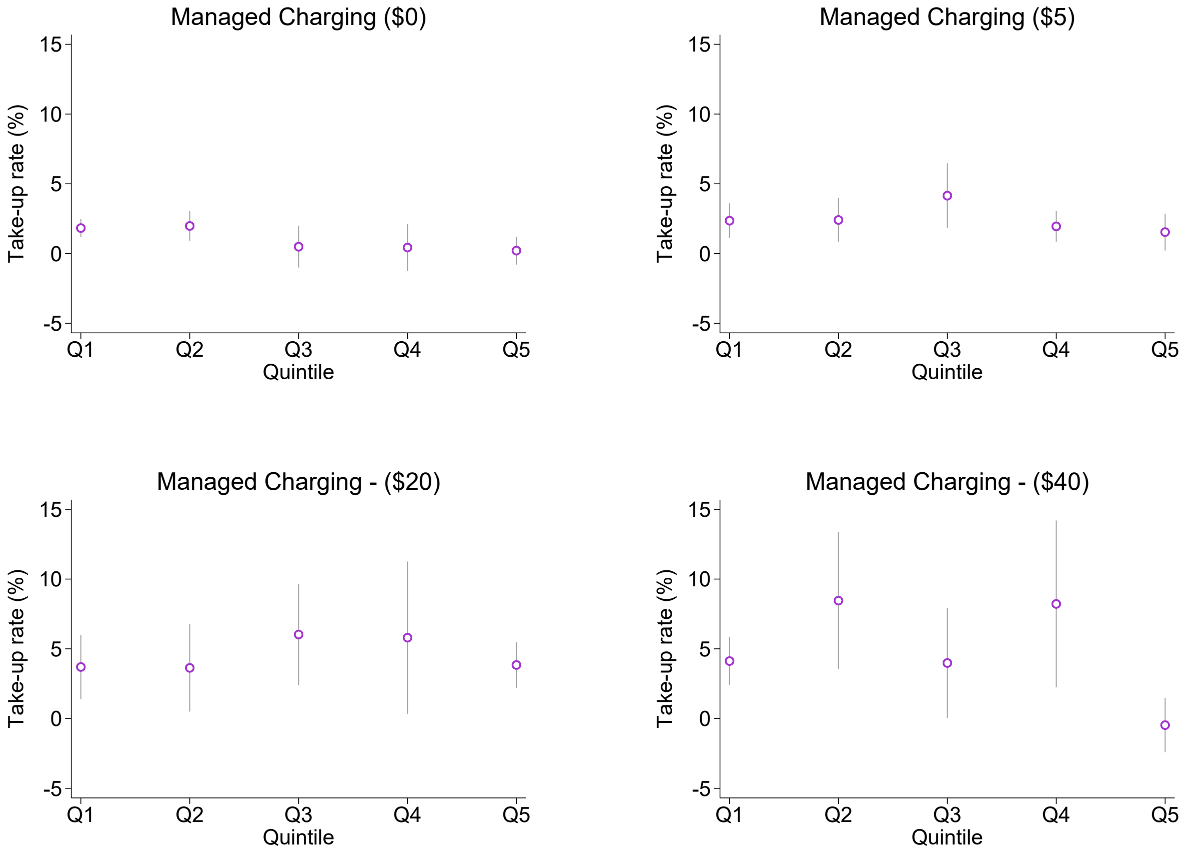
Notes: This table reports enrollment in our treatments, estimated using Equation (1). For the telemetry-only control group (C2), take-up is equal to one for households who enroll in telemetry and zero otherwise. For the four managed charging groups (T1–T4), take-up is equal to one if the household enrolls in managed charging. For the whole-house TOU plus telemetry group (T5), take-up equals one if the household enrolls both in steep TOU and in telemetry. For the whole house TOU only group (T6), take-up equals one if the household enrolls in steep TOU. Finally, EV-only TOU group, take-up equals one if the household enrolls in steep EV-only TOU and telemetry. We exclude control group C1, where take-up is zero by construction. The omitted category is the telemetry-only control group (C2); we present the control mean for this group. All specifications include strata fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.1: Managed charging supply curve with solar households



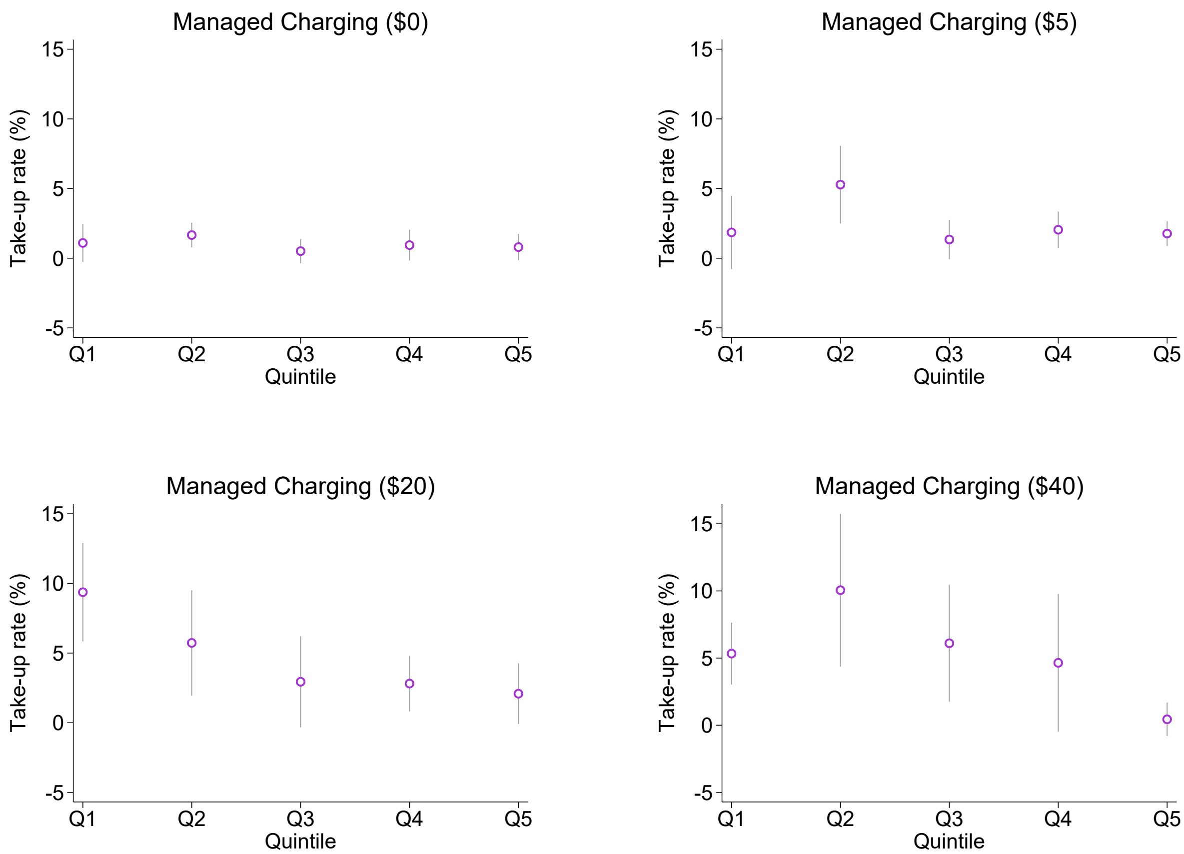
Notes: This figure plots the effect of managed charging incentive offers on enrollment for household including those with solar PV, estimated using Equation (1). Estimates are relative to the pure control group (C2), where take-up is mechanically zero. We plot 95% confidence intervals in light gray.

Figure B.2: Managed charging enrollment by electricity consumption quintile



Notes: This figure plots managed charging enrollment by quintiles of pre-treatment electricity consumption, separately for each treatment arm. The underlying regression includes strata fixed effects. 95% confidence intervals, computed from heteroskedasticity robust standard errors, are shown in light gray.

Figure B.3: Managed charging enrollment by peak electricity consumption share quintiles



Notes: This figure plots managed charging enrollment by quintiles of the share of pre-treatment electricity consumption that occurred during peak hours, separately for each treatment arm. The underlying regression includes strata fixed effects. 95% confidence intervals, computed from heteroskedasticity robust standard errors, are shown in light gray.

B.3 Energy consumption

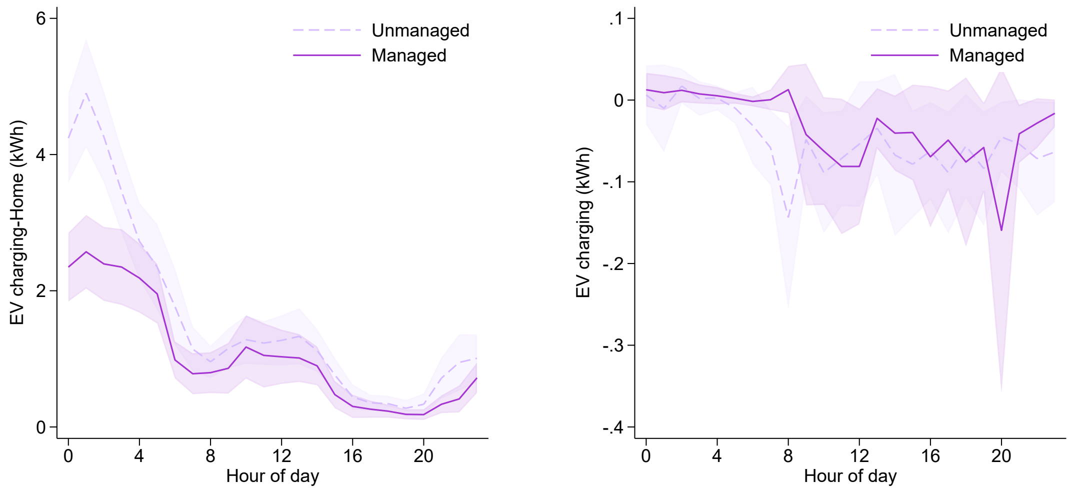
Table B.4: Local average treatment effects of managed charging and TOU on energy use

	(1) kWh
Managed charging takeup	-0.184
	(0.181)
Whole-house TOU takeup	-0.520
	(0.328)
EV-only TOU takeup	-0.232
	(0.210)
Control mean	0.929
Observations	170,020,188

Notes: This table presents instrumental variables estimates of the effects of managed charging, whole-house TOU, and EV-only TOU participation on electricity consumption. The dependent variable is weekly mean kWh of electricity consumption per hour. Treatment takeup is instrumented using randomized offer assignment. The unit of analysis is the household-by-hour observation. All regressions include household, week-of-sample, and hour-of-day fixed effects. The omitted category is control group C2. Standard errors, in parentheses, are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Association between managed charging and energy use

Figure B.4: Association between (managed) charging and electricity use, home vs. away



Notes: This figure plots the relationship between energy consumption and managed charging (solid purple) and unmanaged charging (dashed purple), compared to no charging. The left panel plots home charging, while the right panel plots away-from-home charging. Note that the two plots are on different y axes. We estimate the relationship using Equation (4). Standard errors are clustered by household, and we present 95% confidence intervals in the shaded area.

C Additional pre-specified results

C.1 Energy consumption

Table C.1: Treatment effects on energy use, unpooled

	(1)
	kWh
Managed charging offer ($0)	-0.00663
	(0.00545)
Managed charging offer ($5)	0.00186
	(0.00753)
Managed charging offer ($20)	-0.00555
	(0.0117)
Managed charging offer ($40)	-0.00544
	(0.0104)
Whole-house TOU offer + Telemetry	-0.00213
	(0.00705)
Whole-house TOU offer	-0.0202*
	(0.0104)
EV-only TOU offer	-0.00837
	(0.00806)
Control mean	0.929
Observations	170,020,188

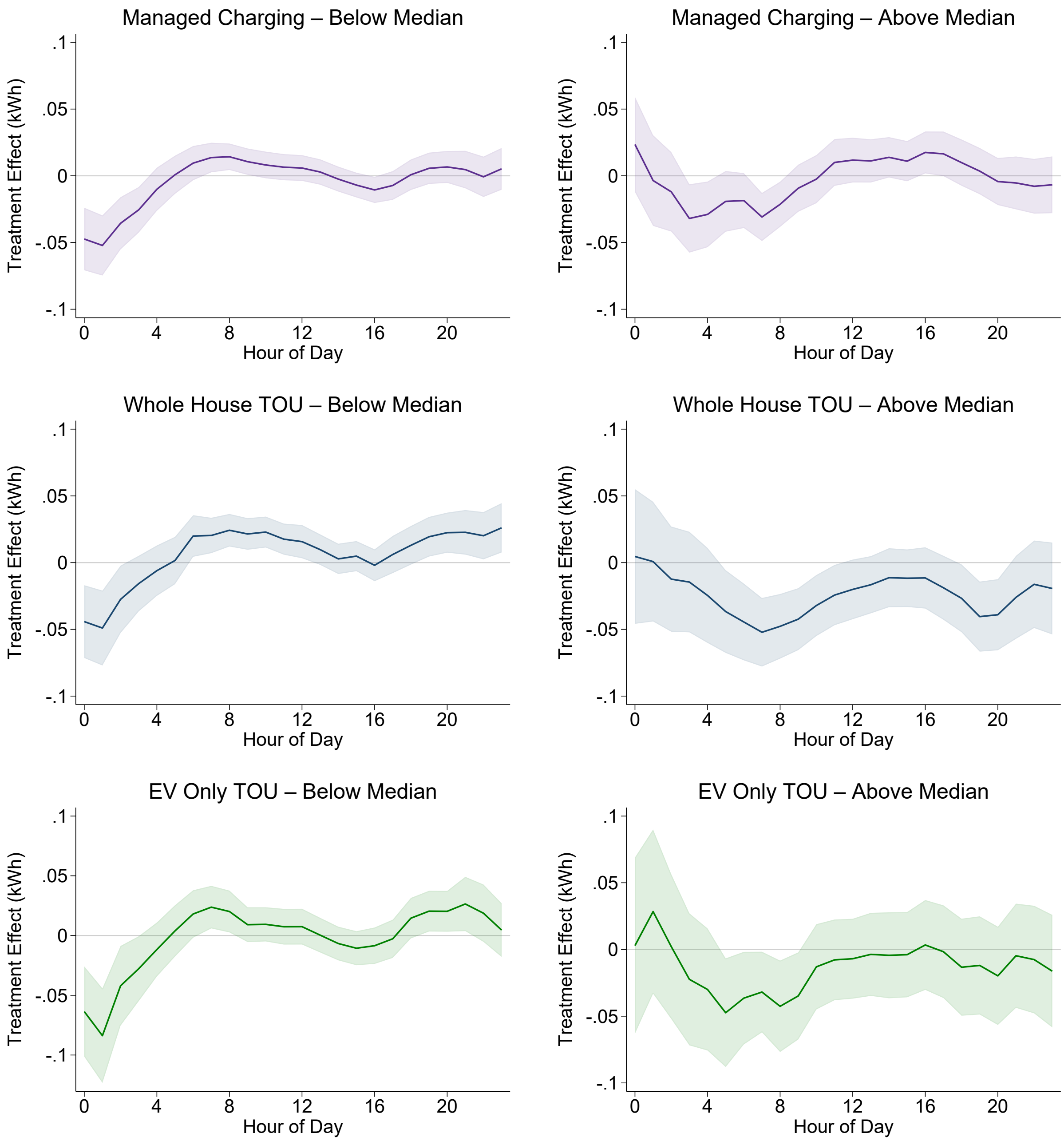
Notes: This table presents the overall intent-to-treat effects of each treatment arm on electricity consumption. The dependent variable is weekly mean kWh of electricity consumption per hour. The unit of analysis is the household-by-hour observation. All regressions include household, week-of-sample, and hour-of-day fixed effects. The omitted category is control group C2. Standard errors, in parentheses, are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Treatment effects on energy use, logs

	(1)
	log(kWh)
Managed charging offer ($0)	0.00284
	(0.00606)
Managed charging offer ($5)	0.00402
	(0.00707)
Managed charging offer ($20)	0.00769
	(0.00865)
Managed charging offer ($40)	-0.00697
	(0.0146)
Whole-house TOU offer + Telemetry	-0.00131
	(0.00729)
Whole-house TOU offer	-0.000159
	(0.00773)
EV-only TOU offer	-0.00159
	(0.00830)
Control mean	-0.632
Observations	168,884,629

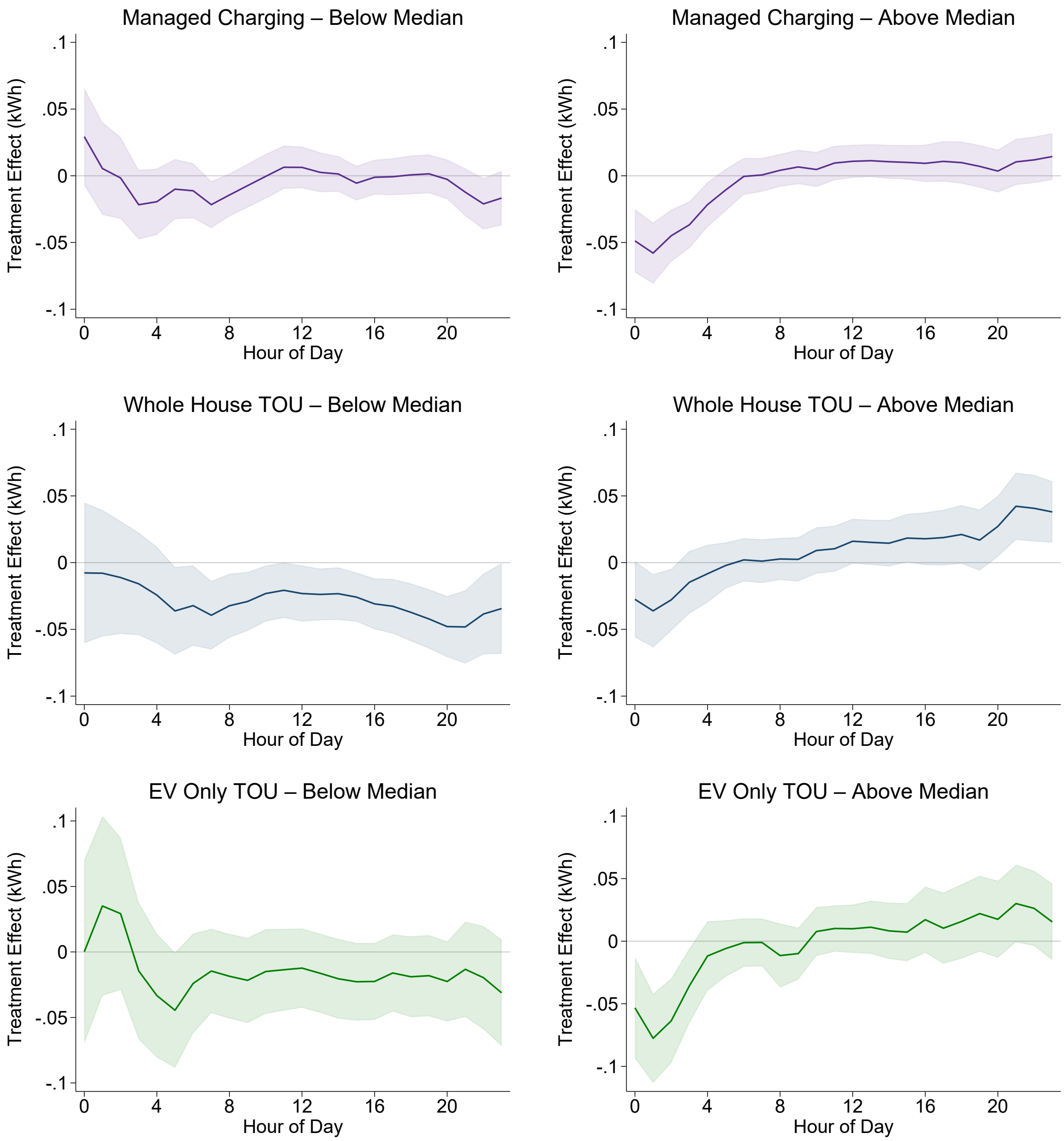
Notes: This table presents the overall intent-to-treat effects of each treatment arm on electricity consumption in logs. The dependent variable is the log of weekly mean kWh of electricity consumption per hour. The unit of analysis is the household-by-hour observation. All regressions include household, week-of-sample, and hour-of-day fixed effects. The omitted category is control group C2. Standard errors, in parentheses, are clustered at the household level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.1: ITT effects: Heterogeneity by total consumption



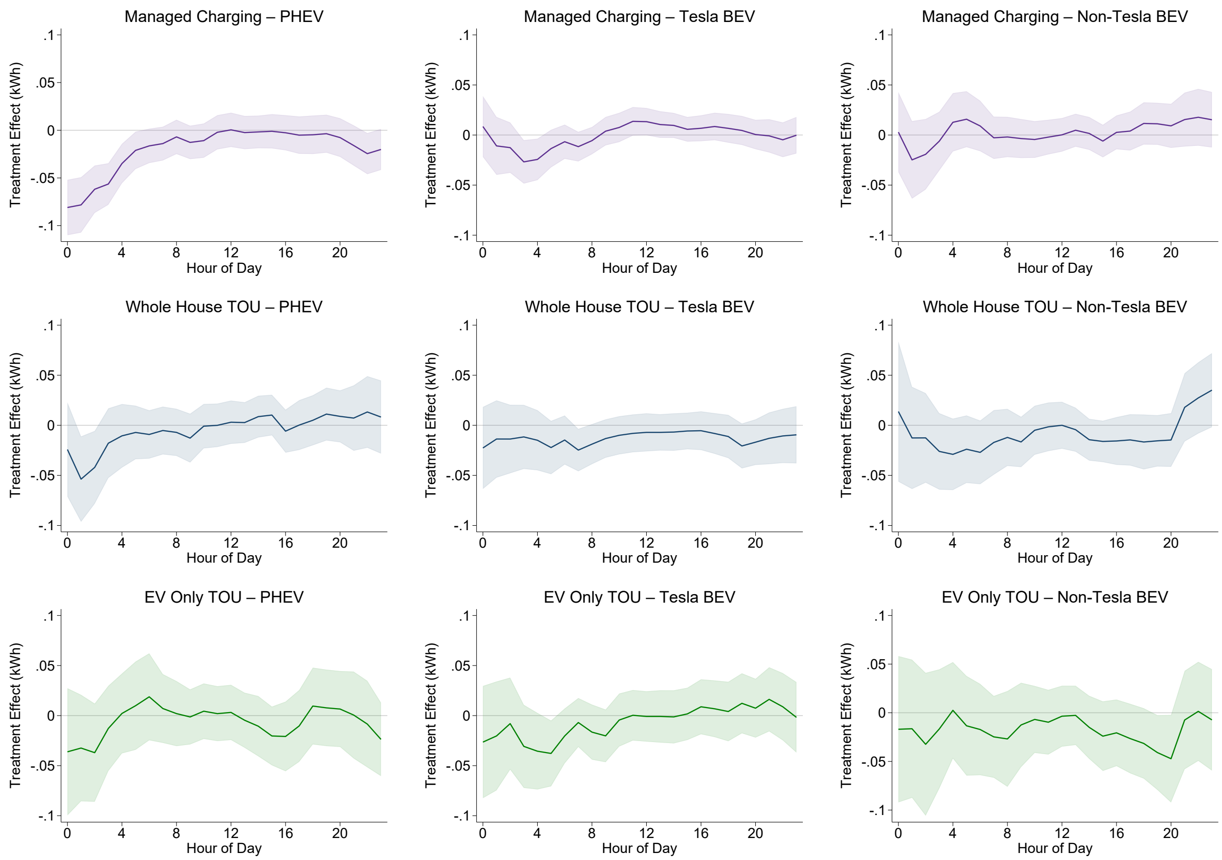
Notes: This figure plots heterogeneous ITT effects, split by whether the household's total pre-treatment electricity consumption was below or above the median. All panels are estimated using the same regression, which includes household, week-of-sample, and hour-of-day fixed effects. The omitted category is control group C2. Standard errors, in parentheses, are clustered at the household level; we show 95% confidence intervals in shaded bands.

Figure C.2: ITT effects: Heterogeneity by peak consumption share



Notes: This figure plots heterogeneous ITT effects, split by whether the household's share of pre-treatment electricity consumption that occurred during peak hours was below or above the median. All panels are estimated using the same regression, which includes household, week-of-sample, and hour-of-day fixed effects. The omitted category is control group C2. Standard errors, in parentheses, are clustered at the household level; we show 95% confidence intervals in shaded bands.

Figure C.3: ITT effects: Heterogeneity by vehicle type



Notes: This figure plots heterogeneous ITT effects, split by whether the household has a PHEV (left column), Tesla BEV (central column), or non-Tesla BEV (right column). All panels are estimated using the same regression, which includes household, week-of-sample, and hour-of-day fixed effects. The omitted category is control group C2. Standard errors, in parentheses, are clustered at the household level; we show 95% confidence intervals in shaded bands.

D Deviations from our pre-analysis plan

This experiment was pre-registered in the AEA RCT registry under Identification No. AEARCTR-0014013. Though we endeavor to follow the PAP as closely as possible, we enumerate our limited deviations below:

- **Sample:** Though we did not describe this in the PAP, we restrict the sample to customers without solar panels only. This is because we do not fully observe electricity consumption for these households, only consumption net of solar generation.
- **Analysis:** In our PAP, we specified that we would estimate treatment effects on a several different measures of program enrollment. In practice, these are virtually identical to the estimates we present in Appendix Table 2, so we omit them for brevity.
- **Analysis:** In our PAP, we specified that we would measure willingness-to-accept using our auction treatment. The number of households who responded to the survey for this treatment was vanishingly small, so we omit all auction-related analysis.
- **Analysis:** In our PAP, we specified that we would measure the correlation between households' experiences with the program and disenrollment. We omit this, because (i) we were unable to collect survey data on household satisfaction, and (ii) we see extremely limited evidence of disenrollment.
- **Analysis:** In our PAP, we specified that we would measure price elasticities of demand using variation coming from our TOU steepening treatments. Because enrollment in these treatments was extremely low, these regressions do not have meaningful information content and we omit them.
- **Analysis:** In our PAP, we pre-specified that we would estimate the effect of our managed charging offers and TOU price steepening within our charging data. Relatedly, we pre-specified tht we would use a matching approach to compare EV charging behavior in observably-similar households between our groups with telemetry data. Because there appears to be substantial selection into the telemetry dataset, and because the set of customers who enroll in managed charging is very small and likely highly selected, we instead use the non-experimental estimator described in Equation (4). This specification includes household fixed effects, which allows us to address cross-sectional selection concerns by comparing periods of managed charging vs. unmanaged charging vs. no charging within household.