Electric Vehicles and the Energy Transition: Unintended Consequences of a Common Retail Rate Design *

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Abstract

The growth of electric vehicles (EVs) raises new challenges for electricity systems. We implement a field experiment to assess the effect of time-of-use (TOU) pricing and managed charging on EV charging behavior. We find that while TOU pricing is effective at shifting EV charging into off-peak hours, it unintentionally induces new and larger "shadow peaks" of simultaneous charging. These shadow peaks lead to greater exceedance of local capacity constraints and advance the need for distribution network upgrades. In contrast, centrally managed charging solves the coordination problem, reducing transformer capacity requirements, and is well-tolerated by consumers in our setting.

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1 Introduction

The transportation sector accounts for almost a quarter of global carbon emissions (IEA, 2023). Consequently, the adoption of electric vehicles (EVs) and transition to low-carbon electricity supply have become key climate mitigation strategies. However, achieving widespread adoption raises concerns about the ability of the existing electricity system to produce and deliver energy where and when it is demanded by EV owners.

Although much attention is focused on the generation side of the industry, it is local distribution networks—the collection of poles, wires, and transformers that connect consumers to the electricity system—that are likely the first bottleneck for EV charging. The challenge is to avoid situations where network capacity limits are exceeded when too many vehicles are charged simultaneously. Given home chargers can draw power up to ten times higher than typical residential devices, it takes just a few vehicles to exceed the traditional capacity limits of a transformer—the last link in the chain, often serving fewer than a dozen homes. Regularly exceeding nameplate capacity causes wear and tear that can cause the transformer to fail and/or accelerate the need for an upgrade (NREL, 2024). This local issue is enhanced by the fact that early EV adopters tend to be geographically concentrated (Elmallah et al., 2022), meaning that local capacity restrictions can bind even at low levels of overall EV adoption.

A key policy question is whether grid upgrades—and their costs—can be delayed by incentivizing households to shift charging to times when there is less strain on existing infrastructure. An increasingly common solution is Time-of-Use (TOU) pricing, which features higher prices during "peak" periods of predictable high demand, and cheaper prices during "off-peak" periods.[1] However, while TOU pricing has been shown to be effective in shifting the timing of EV charging (Bailey et al., 2024; La Nauze et al., 2024), we consider a potential unintended consequence. By incentivizing charging during specific cheap hours, the likelihood of coincident charging could increase, resulting in large "shadow peaks" in pockets of the distribution network where EVs are prominent.[2] As a result, TOU pricing runs the risk of being

[1]TOU pricing is increasingly being offered and adopted in the United States, for example. In 2023, 45% of residential customers lived in a utility region with a residential TOU rate offering (EIA, 2024). In these regions, 14% of customers were enrolled in a time-varying rate, up from 3% in 2015 (Faruqui et al., 2019)

[2]Most EVs allow owners to schedule charging via apps. Many apps include features to prioritize charging in a location's prevailing cheaper TOU time periods, thus making this concentration more

a policy that, while well-intentioned and effective at reducing costs in one part of the electricity system (i.e. generation costs), could exacerbate strain and ultimately increase costs in another part (i.e. distribution networks).

To investigate this possibility, we run a field experiment to analyze the charging behavior of groups of EVs randomly assigned to TOU pricing and an alternative approach of "managed charging", both compared to a baseline of flat pricing. Under managed charging, EV owners provide their desired departure time, and charging is sequenced to prevent multiple vehicles from overloading their transformer.[3] Since our focus is on potential distribution-level impacts, we created "virtual transformers" by grouping sets of 10 EVs from each treatment group *as though* they were connected to the same transformer. This approach allowed us to overcome the current sparsity of EV adoption in our setting and evaluate impacts under a simulated higher penetration of EVs within a distribution network. For each virtual transformer-day, we randomly assigned an empirically-grounded capacity level and compared it to the aggregate EV charging demand, combined with a representative non-EV demand, to evaluate the extent to which transformer capacities were exceeded across treatment groups.

To conduct the experiment, we partnered with FortisAlberta, an electric distribution company in Alberta, Canada, and Optiwatt, a U.S.-based EV charging app. We recruited over 200 EV owners, primarily urban and suburban, and randomly assigned them to either TOU pricing, managed charging, or a control group. TOU participants were informed they would receive 3.5 cents/kWh for charging at home during off-peak hours (10am – 2pm and 10pm – 6am).[4] Managed charging participants were told they would receive 3.5 cents/kWh for all home charging, but their schedules would occasionally be adjusted to meet the needs of the grid. Control participants remained on a flat rate and were not contacted after initial enrollment.

We find that TOU pricing delivers, as intended, a considerable shift in EV charging from peak to off-peak periods—a beneficial outcome for reducing system-wide demand peaks. However, it unintentionally increases off-peak charging coordination, more than doubling transformer capacity violations compared to the Control group, thereby exacerbating strain on the distribution network. In contrast, managed charging outperforms TOU by reducing capacity violations in peak hours without a corre-

likely.

[3]Managed EV charging programs are nascent but growing, with 110 programs launched in the U.S. since 2013 (Black et al., 2024).

[4]All currency is in Canadian dollars unless otherwise noted. At time of writing, \$1 CAD $\approx$ \$0.73 USD.

sponding increase in off-peak violations. A potential drawback of managed charging is that it may be less tolerated by users than TOU pricing. We find that while active users rarely opted out of managed charging events ($< 1\%$), attrition rates were greater in the Managed group than the TOU group. As we detail in what follows, group-specific software issues likely played an important role, but we cannot rule out lower satisfaction with the program.

Previous research has considered the effect of TOU pricing on distribution constraints using simulation studies that rely on representative consumption curves and assumptions of elasticities and coincident charging behavior (e.g., Hilshey et al., 2012; Muratori, 2018; Elmallah et al., 2022; Turk et al., 2024). By using a field experiment, we directly observe consumer behavioral responses across heterogeneous individuals. The use of virtual transformers allows us to compare the impact of these two interventions—TOU pricing and managed charging—on charging coordination under high EV penetration scenarios.

Our results point to a new challenge for demand-side flexibility in electrifying personal transportation and home heating: local distribution network capacity constraints. While distribution network challenges have been well documented in low income countries (Jacome et al., 2019; Carranza and Meeks, 2021; Berkouwer et al., 2024), electrification is now raising similar issues in more mature electricity systems. NREL (2024) forecasts a 160-260% increase in U.S. transformer capacity needs by 2050 to accommodate electrification. Supply chain constraints have recently driven up costs and increased lead times for new transformers, which experts warn are impeding the energy transition (Chopra et al., 2024). Given the massive scale of potential infrastructure investments, minimizing unintended cost increases is imperative. Policies that reduce reliance on transformer upgrades could significantly lower the cost of electrifying transportation.

The existing literature focuses mainly on policies that aim to provide common time-varying (dynamic) price signals to consumers when electricity generation costs or system-wide demand are high (e.g., Harding and Sexton, 2017; Garnache et al., 2024). Dynamic pricing, in which the retail price changes hourly in line with wholesale market conditions, does not resolve the distribution network coordination challenge. Instead, it is likely to make it worse by narrowing the set of inexpensive hours in which to target EV charging. An optimal pricing solution would require the complexity and granularity of being both time-varying and household-specific to properly signal local distribution constraints. In practice, highly granular real-time pricing is rarely adopted by residential customers who are believed to prefer predictable and stable bills (Schittekatte et al., 2024). This is compounded by the political challenges of exposing customers to sustained high-price events such as those experienced during the 2021 Winter Storm event in Texas (Busby et al., 2021). Consequently, a household-specific dynamic price is likely to face resistance from both consumers and regulators.

Rather than focusing on a price signal, managed charging compensates consumers for providing a service: allowing the timing of their charging to be centrally controlled. In doing so, managed charging directly addresses the coordination problem by sequencing charging among nearby households to remain within the limits of local distribution networks. Although managed charging for EVs is currently far less common than TOU pricing, it has the potential to reduce the strain on distribution networks and lower the cost of the transition to electrified transportation.

2 A Simple Model of Distribution Transformer Constraints

To illustrate the intuition behind the EV charging challenge, we draw on a simple model of a distribution transformer capacity requirement developed by Boiteux and Stasi (1964). Consider a distribution transformer, which must be sized sufficiently to meet the maximum aggregate peak demand of the collection of individual consumers it serves. The system planner's objective is to minimize the capacity of the transformer, q_T, subject to meeting the aggregate demand, $\sum_i^n q_i$, of the downstream consumers under all conditions and in all hours. If undersized, the distribution equipment will frequently operate beyond its capacity, causing stress and degradation that can result in failure and the need for premature replacement. Conversely, oversizing the transformer leads to unnecessary and inefficient added costs.

The challenge faced by the planner is that the collective demand is uncertain, and thus best thought of as a probability distribution. Accordingly, Boiteux and Stasi (1964) propose a sizing rule that incorporates both the average value ($\bar{q}$) of potential aggregate demands faced by the transformer plus an "irregularity margin" equal to the variability of collective peak demand (σ) times a margin (λ). The greater the irregularity of the collective demand, the larger the transformer must be sized:

$$q_T = \bar{q} + \lambda\sigma \tag{1}$$

Equation (1), however, does not sufficiently describe the underlying behavior of individual consumers. Consider, for example, that at an individual level, it matters whether a customer's irregularity occurs coincident with their neighbor's or at a completely different time. The irregularity margin can thus be described as a function of individual irregularities, σ_i, and a correlation parameter, K_i, that reflects the tendency of any individual's irregularity to occur coincident with that of the collective. This results in a complete expression of the distribution transformer capacity requirement as a function of individual consumer demands:

$$q_T = \sum_i (\bar{q}_i + \lambda K_i \sigma_i) \tag{2}$$

From this expression, we see the factors that increase distribution transformer capacity requirements, and thus costs on the system:

1. q_T increases with average peak demand, $\bar{q}_i$;
2. q_T increases as individual irregularities, σ_i, increase; and
3. q_T increases as the correlation across irregularities, K_i, increases.

The first factor is an obvious result, but the second and third are more nuanced and especially relevant to the topic of this paper. EVs, and especially level 2 chargers, significantly increase the irregularity of individual loads, σ_i, due to their high power draw relative to other household appliances. Consider, for example, a non-EV household whose demand is likely to oscillate between 0.5 kilowatts (or less) and 5 kW over the course of a day. A home with a level 2 charger, which has a power draw that can range from 5 to 12 kW, has more than double the potential peak power draw and therefore a significantly larger σ_i. The issue of increased correlation of irregularities is less clear with EV charging. By separating energy demand (charging) from EV service (driving), it is not clear *ex-ante* that K_i increases in a world with more EVs. This is where TOU pricing can play an unintentional role in increasing the correlation of charging. By creating a coordinating mechanism to target a narrow set of hours with cheaper priced blocks, TOU pricing could increase K_i and thus raise the transformer capacity requirement and, ultimately, distribution system costs. In contrast, managed charging has the potential to reduce charging correlation.

3 Experimental Design and Data

Recruitment and Treatment Randomization

In early 2023, households with EVs in FortisAlberta's territory were recruited for the "EV Smart Charging Pilot" via social media and other advertising methods.[5] Participants were required to download the Optiwatt app, connect it to their EV through a wireless telemetry connection, and sign up for the program through the app. They received \$50 for enrolling and \$100 for completing the program at the end of 2023. The app automatically tracked EV charging, both at home and away. While Optiwatt offers additional features, participants in the study were limited to using it to monitor their charging and setting their desired charge levels and departure times.

The 202 EVs we recruited are primarily located in suburban and urban regions near Edmonton and Calgary, with only 14% in rural regions (Statistics Canada, 2024). Comparing participants' charging behavior to drivers in nine major U.S. cities using the Optiwatt app, we find that their behavior is broadly representative of current EV owners across North America.[6]

In July 2023, after several months of monitoring charging behavior, we randomized EV owners into three groups: (i) Control (62 EVs), (ii) TOU (70 EVs), and (iii) Managed (70 EVs).[7] TOU and Managed participants were defaulted into their treatment group and informed their incentives would begin July 5, 2023, the start of the treatment period. The Control group received no messaging and continued to be monitored through the end of 2023. For details on participant messaging, see Appendix A.

TOU participants were offered a 3.5¢/kWh reward (paid via the Optiwatt app) for at-home charging during "off-peak" hours (10 a.m.–2 p.m. and 10 p.m.–6 a.m.), effectively reducing the variable price by about 19%. Managed participants were offered 3.5¢/kWh for all at-home charging, with the condition that Optiwatt could adjust charging times to align with grid needs. The software ensured EVs met user-set charge targets by their scheduled departure times. Participants could override managed charging and charge immediately using a "Charge Now" button in the app

[5] Fortis serves over 60% of Alberta's electricity distribution network, with over 600,000 end-users. Residential households in its territory face time-invariant retail rates that can vary at most monthly.

[6] The U.S. sample charges slightly longer daily (50 minutes more), but average daily energy charged (22.3 kWh vs. 23.2 kWh) and peak power drawn (6.7 kW vs. 6.8 kW) are nearly identical, indicating similar grid demands (Appendix C.2).

[7] Randomization at the household-level ensured that households with multiple EVs were assigned to the same treatment group.

but forfeited the reward for that day.

Virtual Transformers

To overcome the current sparsity of EVs connected to physical transformers and understand the potential impact of EV charging on the distribution network with a larger number of EVs, we introduced "virtual transformers." We randomly assigned households within the same treatment groups to virtual transformers of 10 cars and analyze their aggregate behavior.[8]

Optiwatt passively monitored EV charging behavior in both the Control and TOU groups without participants' awareness of virtual transformers, which served solely to document group-level constraint violations. In contrast, virtual transformers were integral to Optiwatt's managed charging algorithm for the Managed group. Here, charging was actively sequenced among EVs sharing a virtual transformer to ensure all vehicles reached their charge targets by their scheduled departure times while adhering to transformer capacity limits. When grid constraints or high charging demand made this infeasible, constraint violations were permitted. It is important to note that real-world constraint violations do not necessarily translate into outages. Distribution transformers are capable of handling loads up to 200% of their nameplate capacity for short durations. However, sustained or frequent overloading significantly shortens the transformer's lifespan and increases the likelihood of failure (NREL, 2024). We monitored and recorded constraint violations as a primary object of interest for all groups.

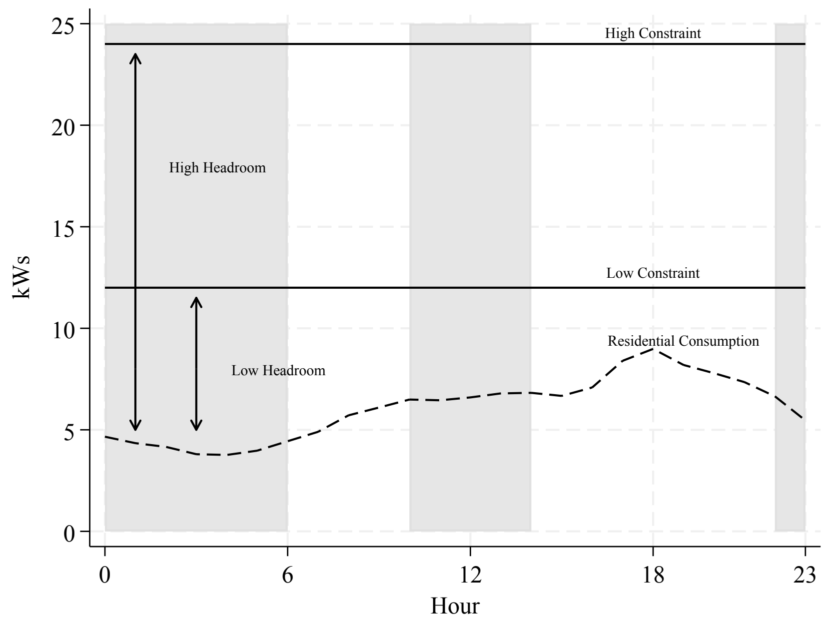
For each virtual transformer-day, we calculated the available headroom for EV charging as the difference between a randomly assigned transformer capacity and representative hourly non-EV demand. Figure 1 displays the hour-specific representative residential household-level load profile in Fortis' territory, multiplied by 10 to represent the 10 households on the virtual transformer.

The daily transformer capacity limits were drawn from a distribution ranging from 12 to 24 kW.[9] These transformer capacity limits were empirically-grounded based on typical distribution transformer ratings (Hilshey et al., 2012; EnergyHub, 2023). The

[8]There were 7 virtual transformers for both the TOU and Managed groups and 6 for the Control group. We included one additional Control transformer with only 2 EVs, adjusting its capacity accordingly. We undertake robustness checks excluding this group and our conclusions are unchanged.

[9]Our distribution of virtual transformer constraints weighted tight constraints more heavily than relaxed constraints, to ensure that the managed charging algorithm was binding a sufficient proportion of time, for statistical power.

Figure 1. Illustration of Virtual Transformer Capacity



Note. Shaded areas represent off-peak hours

difference between the transformer capacity limits and underlying household demand defines the headroom available for EV charging. Capacity is most constrained during the evening peak and increases overnight into early morning hours.

Randomizing transformer capacity limits across a range of values helps address the limitation of relying on a single representative load profile for non-EV demand. Real-world non-EV load variability creates fluctuating periods of slack and tightness in charging headroom. Our range of constraints captures this variability, allowing scenarios where one to three Level 2 EV chargers can operate simultaneously.

Data and Assessment of Balance

Our data span from April 1 to December 13, 2023, covering each charging session's start/end times, kWh charged, charger power (kW), and location (home or away). We also have information on vehicle characteristics, including make, model, year, and battery range.

We use pre-treatment data to check balance across groups by comparing average EV charging metrics and vehicle characteristics. Table 1 shows the groups are well-balanced, with no statistically significant differences in means based on a one-way ANOVA test.

During the experiment, 32 vehicles exited: 20 from the Managed group, 9 from the TOU group, and 3 from the Control group. This may indicate a potential drawback of managed charging, as users in this group may have been less satisfied. However, it is difficult to draw definitive conclusions about the relative acceptance of managed charging due to software challenges primarily affecting the Managed group. Specifically, Tesla's lack of third-party API support for most of the experiment caused complications, leading to nine Tesla vehicles in the Managed group losing connection with the Optiwatt App due to "user password errors". These errors occurred because repeated attempts by Optiwatt to access Tesla's system were blocked, prompting users to reset their passwords. Reconnecting required users to reset passwords in both systems, a step these attrited users did not complete. This issue had a greater impact on the Managed group because the management algorithm required more frequent API interactions.

Only one Control group participant and no TOU participants left due to user password errors. Excluding user password errors, attrition rates between TOU and Managed are not statistically different, though both exceed that of the Control group. In Appendix B, we compare observables for vehicles that dropped out versus those that remained and find the charging behavior is largely comparable.[10] Estimated experimental treatment effects over time also remain consistent despite attrition.

Nevertheless, we take seriously the possibility that participants in the Managed group may have been closer to the margin of exiting the program than others, making them not bother to solve the password reset error. This type of attrition reduces the benefits of managed charging relative to the other programs. To account for this, we perform a bounding exercise, described in section 5.2, where attrited vehicles are assigned Control group behavior to calculate treatment effects.

4 Descriptive Statistics

We begin with a descriptive analysis of changes in charging behavior and transformer violations across the three groups, comparing outcomes before and after treatment. The lefthand side of Figure 2 shows mean hourly charging (kWh) across vehicle-days with non-zero home charging by group.[11] The shaded areas indicate off-peak hours.

[10]The proportion of home charging, charge duration, energy charged (kWh), share of off-peak charging, and proportion of Teslas are statistically indistinguishable between attritors and stayers in both the pre- and post-treatment periods. However, the maximum charging rate (kW) is significantly higher post-treatment for attritors (8.60 kW) compared to non-attritors (6.99 kW).

[11]A "day" spans 9:00am to 8:59am to capture overnight charging decisions.

Table 1. Balance on Observable Characteristics by Group Using Pre-Treatment Data

Variable	Control	TOU	Managed	ANOVA (p-value)
Home Share (%)	74.25	77.71	74.27	0.62
	(26.55)	(21.14)	(23.97)	
Charge Duration (Minutes)	242.62	236.74	262.04	0.63
	(161.39)	(132.06)	(185.14)	
Energy Charged (kWh)	22.65	22.45	21.70	0.85
	(9.31)	(9.43)	(11.56)	
Max kW Charge (Power)	6.85	6.94	6.38	0.37
	(2.24)	(2.51)	(2.75)	
Off-Peak Share (%)	53.69	48.25	48.80	0.17
	(19.31)	(17.51)	(17.55)	
Off-Peak Share (%) - Home Only	54.76	49.53	51.54	0.37
	(22.60)	(20.92)	(20.80)	
Tesla (%)	83.87	87.14	84.29	0.85
	(37.08)	(33.71)	(36.66)	
Number of EVs	62	70	70	
Number of Virtual Transfomers	6	7	7	

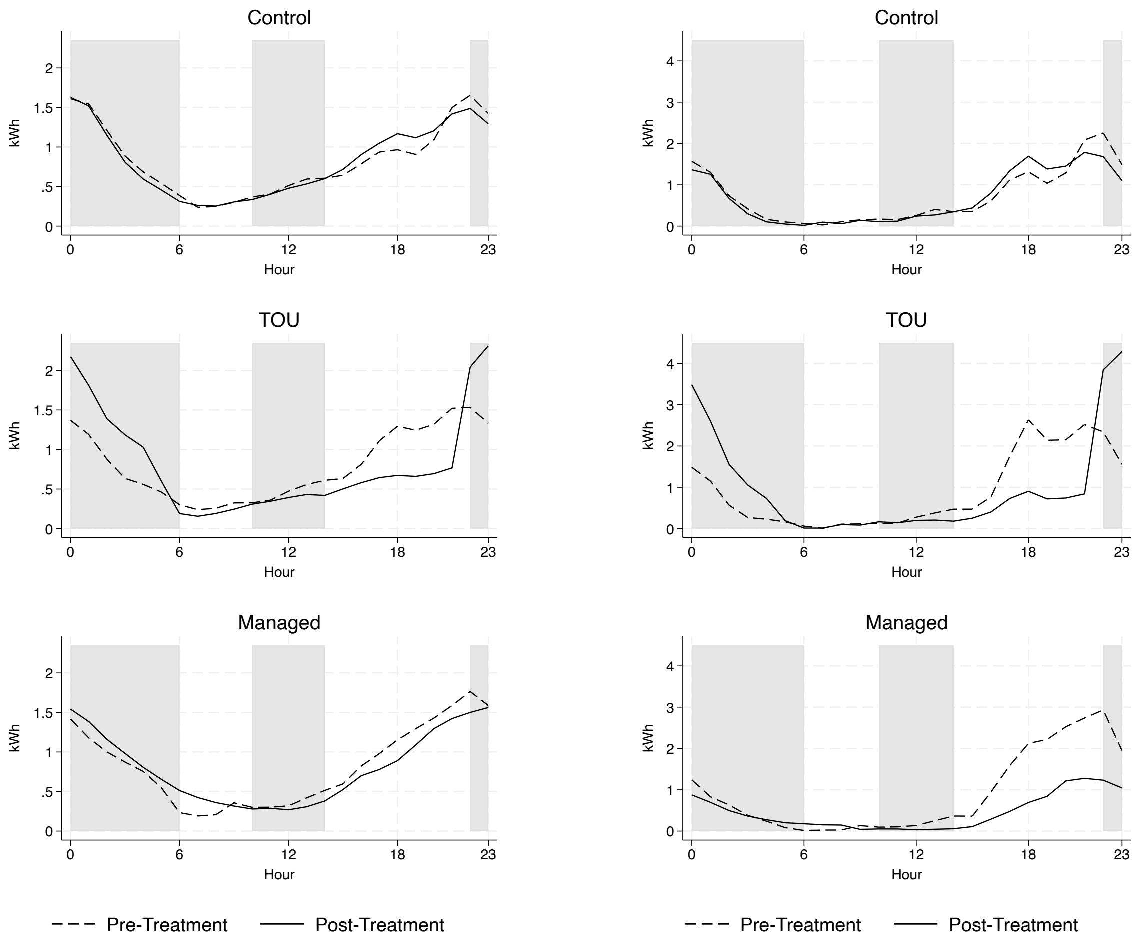
Notes. This table compares pre-treatment average values of various charging variables at the vehicle-level by group. Parentheses contain the standard deviations. Home Share represents the percentage of total charging kWh at home, Charge Duration is the daily number of minutes the EV is charged at home, Energy Charged is the kWh charged per day at home, Max KW Charge is maximum power of charge used per day at home, Off-Peak Share is the percentage of kWh charged in the off-peak either at home or away, and Off-Peak Share - Home Only is the percentage of kWh charged in the off-peak at home only. Tesla is the percentage of EVs that are Tesla and Number of EVs is the count of EVs. ANOVA (p-value) reports the p-value from one-way ANOVA tests for differences in means across groups.

Pre-treatment charging profiles are similar across groups, with higher mean charging starting at 6pm and continuing overnight.

The Control group shows no change in charging behavior between pre- and post-treatment, reflecting the absence of incentives for this group. In contrast, the TOU group exhibits a notable increase in charging during off-peak hours and a reduction during the evening peak (5pm–10pm), suggesting a response to financial incentives. The Managed group shows modest changes: a slight reduction in peak period charging and a slight increase in early morning off-peak charging. This pattern aligns with the managed charging algorithm's goal of distributing charging within the available distribution transformer capacity, rather than focusing on shifting charging from the peak to off-peak.

The righthand side of Figure 2 summarizes the average hourly distribution trans-

Figure 2. Average Charge kWh and Transformer Violations by Group and Hour



(a) Average Charged kWh

(b) Average Transformer Violations

Notes. Average Charged kWh reflects the mean hourly charging (kWh) across all vehicle-days with non-zero home charging. Average Transformer Violations represents the average magnitude of hourly transformer constraint violations (in kWh) across all virtual transformers by treatment group, for the pre- and post-treatment periods. The shaded areas indicate off-peak hours.

former constraint violations (in kWh) by group pre-and post-treatment. Pre-treatment, each group shows higher constraint violations in the evening, when EV owners typically return home from work and begin charging. The increased evening demand coupled with tighter transformer headroom during early evening hours (as shown in Figure 1), contributes to these higher violations.

Comparing pre- to post-treatment, we see consistent patterns of constraint violations for the Control group. In contrast, the TOU group displays a sharp increase in constraint violations post-treatment at the beginning of the off-peak period coupled with a decrease during evening peak hours. The magnitude of off-peak violations exceeds those in the peak period pre-treatment, demonstrating that TOU has the potential to accelerate the need for transformer upgrades. In contrast, the Managed group shows a consistent reduction in violations post-treatment. Unlike the TOU group, they reduced peak violations without any corresponding increase in off-peak hours.

5 Empirical Strategy and Results

5.1 Charge Timing and Constraint Violations

The descriptive evidence suggests that treatment incentives affected charging behavior and, consequently, distribution transformer constraint violations. We use a regression analysis to more formally quantify these effects. We begin by analyzing the treatment effects on the timing of at-home charging using vehicle level data.[12]

We estimate the effects of the treatments on hourly charging during peak and off-peak periods, using the following specification:

$$\begin{aligned} Y_{idh} = {} & \beta_0 + \beta_1 \, \text{Post}_d \times \text{TOU}_i + \beta_2 \, \text{Post}_d \times \text{Managed}_i \\ & + \beta_3 \, \text{TOU}_i \times \text{OffPeak}_h + \beta_4 \, \text{Managed}_i \times \text{OffPeak}_h \\ & + \beta_5 \, \text{Post}_d \times \text{OffPeak}_h + \beta_6 \, \text{Post}_d \times \text{TOU}_i \times \text{OffPeak}_h \\ & + \beta_7 \, \text{Post}_d \times \text{Managed}_i \times \text{OffPeak}_h + \alpha_i + \delta_d + \tau_h + \epsilon_{idh} \end{aligned} \tag{3}$$

where Y_{idh} represents the hourly charge (in kWh) ("Charge kWh") for EV i on day-of-sample d and hour-of-day h.[13] Post_d is an indicator that equals 1 starting on July 5,

[12]The majority of charging takes place at home (see Table 1). Additionally, given our focus on local distribution constraints, at-home charging is the relevant measure of interest. Appendix C.1 provides evidence that drivers did not shift charging locations post-treatment.

[13]For this analysis, we include all vehicle-days, not just those with non-zero at home charging as

2023 (post-treatment) and 0 otherwise. Managed_i and TOU_i are indicator variables that denote whether EV i is in the Managed or TOU groups, respectively. Off Peak_h equals 1 if hour h falls within our definition of off-peak hours and 0 otherwise.

We include EV-level fixed effects, α_i, to account for time-invariant charging characteristics specific to each EV. Additionally, we incorporate hour-of-day fixed effects, τ_h, and day-of-sample fixed effects, δ_d, to control for time-varying factors within days and over time, that may influence charging behavior.

The treatment effects for TOU are represented by β_1 for peak hours and $\beta_1 + \beta_6$ for off-peak hours. Likewise, the Managed treatment effects are represented by β_2 for peak hours and $\beta_2+\beta_7$ for off-peak hours. For vehicles in the TOU and Control groups, standard errors are clustered at the EV level, as these vehicles do not interact with one another within a virtual transformer. For vehicles in the Managed group, standard errors are clustered at the transformer level to account for correlated errors within a transformer arising from the managed charging algorithm, as well as autocorrelation.[14]

Column (1) of Table 2 reports the treatment effects during peak and off-peak periods for hourly charging. The TOU group exhibits large and significant effects in both reducing peak period charging and increasing off-peak charging. Peak charging decreases by 55% relative to the Control group's post-treatment mean ($-0.203/0.369 \approx -0.55$) while off-peak charging increases by 54% ($0.229/0.422 \approx 0.54$). In contrast, the effects for the Managed group are smaller and not significant. These results are consistent with the descriptive evidence in Figure 2, where TOU shows a sizable shift to off-peak hours, while the Managed group does not exhibit a distinct change.

The middle panel of Table 2 presents the results of Wald tests assessing the null hypothesis that the estimated treatment effects for TOU and Managed are equal. We report the differences in treatment effects, with p-values shown in brackets. For both peak and off-peak, the differences are statistically significant.

We now examine how treatments affected transformer capacity violations, shifting focus from individual EV charging behavior to aggregated transformer-level impacts. This analysis captures how changes in charging behavior influence the coincidence of EV charging on the same virtual transformer. We aggregate the individual EV data to the transformer level and estimate a model analogous to equation (3) with i indexing transformers instead of vehicles and the dependent variable being the magnitude of

in Figure 2.

[14]Appendix C.3 provides results clustering at the vehicle-level for all treatment groups, with somewhat tighter standard errors.

Table 2. Estimated Treatment Effects by Group

Group	Hours	(1) Charge kWh	(2) Constraint Violations
TOU	Peak	-0.203	-0.772
		(0.041)	(0.174)
	Off-Peak	0.229	0.961
		(0.047)	(0.277)
Managed	Peak	-0.048	-0.720
		(0.029)	(0.176)
	Off-Peak	0.062	-0.146
		(0.040)	(0.097)
Treatment Effect Comparison			
TOU - Managed	Peak	-0.155	-0.052
		[0.000]	[0.826]
	Off-Peak	0.167	1.108
		[0.001]	[0.001]
Mean Dep. Var. (Post-Treatment)			
Control	Peak	0.369	0.906
	Off-Peak	0.422	0.689
Observations		1,131,426	127,512

Notes. This table provides the estimated treatment effects for the EV-level dependent variable Charge kWh and the transformer-level dependent variable Constraint Violations (in kWh), using at-home charging only. The estimated treatment effects are separated into Peak and Off-Peak hours. Treatment Effect Comparison compares the treatment effects for TOU and Managed by Peak and Off-Peak, with p-values reported in the brackets for the Wald tests assessing the null hypothesis that the estimated treatment effects for TOU and Managed are equal. The Mean Dep. Var. (Post-Treatment) represents the mean value of each dependent variable between April 1, 2023 - July 4, 2023 for the Control group, separated into Peak and Off-Peak hours. All specifications include fixed effects at the day-of-sample, and hour-of-day level. The Column (1) specification includes EV-level fixed effects while the Column (2) includes transformer-level fixed effects. Standard errors (in parentheses) in Column (1) are clustered at the transformer level for vehicles assigned to Managed and the EV-level for vehicles assigned to Control and TOU. Standard errors in Column (2) are clustered at the transformer level.

transformer constraint violations (in kWh) for transformer i on day d at hour h.[15] Additionally, instead of EV fixed effects, the model includes transformer fixed effects, reflecting the shift in the unit of observation from EV-hour to transformer-hour. Standard errors are clustered at the transformer level.[16]

[15] Specifically, for each hour of our sample, we sum Charged kWh at-home for all EVs on a transformer and subtract available transformer capacity headroom. Violations are positive when Charged kWh exceeds available headroom, and 0 otherwise.

[16] Appendix C.3 demonstrates that our results are robust to implementing wild bootstrap robust standard errors to address potential concerns of having only 21 transformer clusters.

Column (2) of Table 2 displays the impact of treatments on distribution transformer constraint violations. Both the TOU and Managed groups show significant reductions in peak period constraint violations, decreasing by 85% ($-0.772/0.906$) and 79% ($-0.720/0.906$) of the Control group's mean post-treatment peak constraint violations, respectively. However, the TOU group exhibits a significant 139% ($0.961/0.689$) increase in off-peak constraint violations, while the Managed group shows a small, insignificant reduction in off-peak constraint violations.

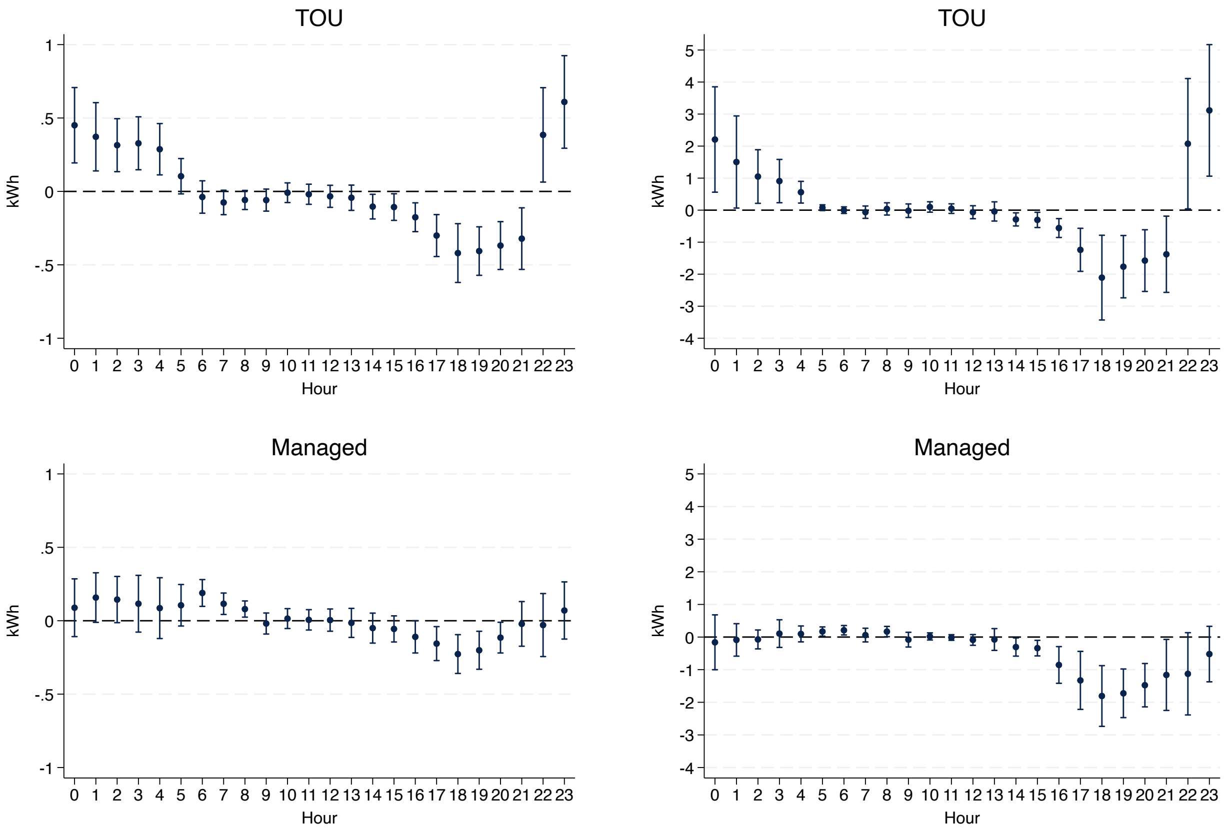
These findings demonstrate that TOU pricing induces a systematic shift in charging away from peak hours and into off-peak hours. While this helps reduce peak period transformer capacity violations, it also results in an increase in coincident charging in off-peak hours and, consequently, the creation of new and more pronounced "shadow demand peaks" on distribution transformers. In contrast, managed charging is able to similarly reduce peak period violations without the commensurate increase in off-peak violations.

To estimate the hourly effect of TOU and Managed, we replace the indicator variable OffPeak_h from equation (3) with a vector of hour indicators for each hour of the day. Figure 3 presents these estimated hourly treatment effects for Charge kWh as the dependent variable. For each hour of the day, the estimates show the difference in Charge kWh between each treatment group and Control during the post-treatment period, compared to the pre-treatment period. For the TOU group, there is a reduction in evening peak period charging and a systematic large and often statistically significant increase in off-peak charging. These results are consistent with EV owners in the TOU group delaying their charging from peak to late evening hours, aligning with financial incentives. In contrast, the Managed group shows a smaller shift away from peak charging. There is a small statistically significant increase in morning charging kWh between 7 AM to 9 AM.[17]

Figure 3 presents hourly regression estimates for our specification using constraint violations as the dependent variable. The results indicate that TOU reduces distribution transformer constraint violations in the evening peak hours (before 10 PM) but leads to a large increase in the magnitude of constraint violations during off-peak evening hours with the coefficients for hours 22 to 4 being significantly different from zero. Several of the positive point estimates in the off-peak evening hours are larger in magnitude than the reductions in the evening peak hours. In contrast, the transform-

[17]The increase in the early morning hours could be driven by the fact that managed EVs are "preconditioned" prior to the set departure time to warm the battery to improve performance.

Figure 3. Estimated Treatment Effects by Group and Hour



(a) Charge kWh

(b) Constraint Violations

Notes. The upper and lower bars represent the 95% confidence interval.

ers with managed EVs experience a significant reduction in violations during evening peak hours with no corresponding increase during off-peak hours.[18]

5.2 Willingness to Provide Automated Flexibility

Our results indicate that managed charging can reduce strain on local distribution networks relative to the status quo (and even more so relative to TOU pricing). However, successful implementation requires a higher customer buy-in compared to TOU rates. Users must consent to and allow third-party control over their charging. It typically also involves sharing charging data with third parties and may require

[18] Appendix C.4 shows that these results become more pronounced as transformer constraints become tighter.

users to download and use third-party apps.

To assess user acceptance, we examine both the intensive and extensive margins. On the intensive margin, we analyzed the frequency of user overrides. In the post-treatment period, across 5,743 instances of managed charging at home, only 44 (less than 1%) were overridden, indicating minimal user interference.

On the extensive margin, we investigate the effects of consumer willingness to remain in the managed program. As noted in Section 3, attrition rates were higher in the Managed group compared to TOU and Control. While technical issues with the Tesla API specific to managed charging may have played a role, participants in the Managed group might also have been more inclined to opt out. To address the impacts of attrition on the effectiveness of managed charging, we conducted a sensitivity analysis. For each vehicle that left the experiment (regardless of treatment group), we randomly assigned the charging behavior of an active Control vehicle for each day following its departure.[19] This analysis yielded results broadly consistent with our main findings, with some attenuation to the estimated effects of managed charging on constraint violations at peak (-0.619) as compared to the main estimate (-0.720); see Table B2. However, the relative increase in off-peak violations for TOU as compared to Managed (1.047) is close to those reported in the main text (1.108), suggesting differential attrition from Managed did not have a strong effect on this comparison.

Finally, to further explore consumer willingness to be involved in managed charging, we conducted a follow-up survey with the Control group. In December 2023, participants were offered the opportunity to join a managed charging program with a variable one-time payment incentive ($0, $75, or $150). Of the 35 respondents, only one declined the offer, suggesting that the incentive levels did not significantly influence participation. Moreover, the retention rate among those who actively opted-in (28 out of 34 remained after 6 months) was comparable to the retention rate of the experimental group that did not experience a password reset error; recall that our initial experimental group was defaulted into managed charging and had the option to opt-out. While our sample is limited to existing EV owners participating in a charging pilot, these findings suggest a substantial willingness to provide flexibility.

[19]This involved a unique random draw with replacement for each attrited car-day.

6 Discussion and Conclusion

As electrification of transportation and other end-uses accelerates, identifying and mitigating impediments to this energy transition will be critical. In this paper, we highlight the importance of local distribution constraints, where the earliest electricity system bottlenecks for EV charging are likely to occur. At a broad geographic scale (e.g. state-wide systems), the diversity of demand across millions of heterogeneous customers makes infrastructure strain less of an issue. However, at the more granular neighborhood scale of the distribution network, load diversity cannot be safely assumed, raising the possibility of correlated charging behavior (Cutter et al., 2021).

We find TOU pricing is effective at shifting EV charging to off-peak hours but it has the unintended consequence of increasing the coincidence of EV charging resulting in increased strain on local distribution networks. Commonly-faced inexpensive time blocks become a coordinating mechanism, leading to "shadow demand peaks" of simultaneous charging and increasing the magnitude of transformer violations as compared to flat pricing. Our experiment demonstrates that this well-intentioned policy is likely to exacerbate the challenge of integrating EVs and accelerate the need for costly infrastructure upgrades. We find that an alternative solution, managed charging, can effectively resolve the coordination problem by sequencing charging to remain within capacity constraints. Additionally, managed charging offers the potential for further benefits, unexplored in our setting, such as responding to peak system demand events and time shifting to co-optimize for both generation costs and distribution constraints.

To quantify the impact on capacity requirements for distribution transformers from our treatments, we compare the average maximum demand on the distribution transformers by group in the post-treatment period. This comparison is agnostic to the transformer constraints chosen in our experiment. Rather, differences between groups reflect the extent of coincidental charging of EVs arising from treatment. The average maximum demand for a 10-EV distribution transformer [i.e., q_T from Equation (2)] under TOU pricing is 24% higher than the Control group post-treatment. In contrast, the average maximum demand for the Managed group is 17% lower than the Control and 33% lower than TOU post-treatment.[20] These results reinforce our findings that managed charging has the potential to reduce the need for distribution

[20] A simulation exercise shows transformer demand increases with the number of EVs, but at a decreasing rate. TOU pricing results in higher maximum demand than the Control group, a disparity that widens as N increases (Appendix C.6).

transformer upgrades compared to the status quo, while TOU can magnify them.

A limitation of our study is the necessary use of virtual transformers versus real-world physical transformers. EV owners connected to the latter are likely to share more similar characteristics than those on our virtual transformers due to their spatial proximity. They may even exhibit similar driving patterns and thus charging demand, e.g. due to living in commuter neighborhoods. As such, one could reasonably expect more correlated behavior in a physical transformer setting. We explore this by re-grouping the passively monitored TOU and Control participants into virtual transformers based on a clustering analysis of similar characteristics. The results of this exercise (detailed in Appendix C.5) confirm the intuition that transformer violations can become more frequent with greater homogeneity. However, this trend holds for both the Control and TOU groups, and, notably, the incremental effect of TOU relative to Control remains consistent with our main estimates.

Although our experiment was conducted in a single province in Canada, the effects we observe of TOU pricing causing a greater concentration of charging are likely to apply across North America more broadly. Our experimentally recovered load shapes align with non-experimental load shapes for drivers on TOU rates across the U.S., which also show a "shadow peak" during off-peak hours immediately following the peak period.[21] Furthermore, our estimates could prove conservative as the 3.5¢ difference between peak and off-peak in our experiment is small relative to other common TOU rates. For example, British Columbia and Ontario have peak to off-peak differences of 10¢ and 22¢, respectively, and California's Pacific Gas & Electric's has EV-specific TOU rates with differences as wide as 36¢ USD (C$0.50) (BC Hydro, 2024; IESO, 2023; PG&E, 2024). An expectedly larger response to the larger real-world price differences is likely to amplify the TOU effect observed in this study.

As the electricity system evolves, flexibility will be increasingly valuable. Smart grid technologies and telemetry control solutions, such as managed charging, offer innovative ways to overcome traditional infrastructure challenges and lower the cost of the transition to electrified transportation. While we observe minimal overrides by managed participants, we note potentially higher attrition in this group. Further study is warranted on consumer acceptance to managed charging programs. However, if broad acceptance and deployment of managed charging is achieved, it could play a significant role in lowering the cost of electrifying transportation.

[21] See Valdberg et al. (2022) for drivers on TOU rates in California's Pacific Gas and Electric service territory and Appendix C.2 for drivers in 14 major US cities using the Optiwatt App, who self-report being on a TOU rate.

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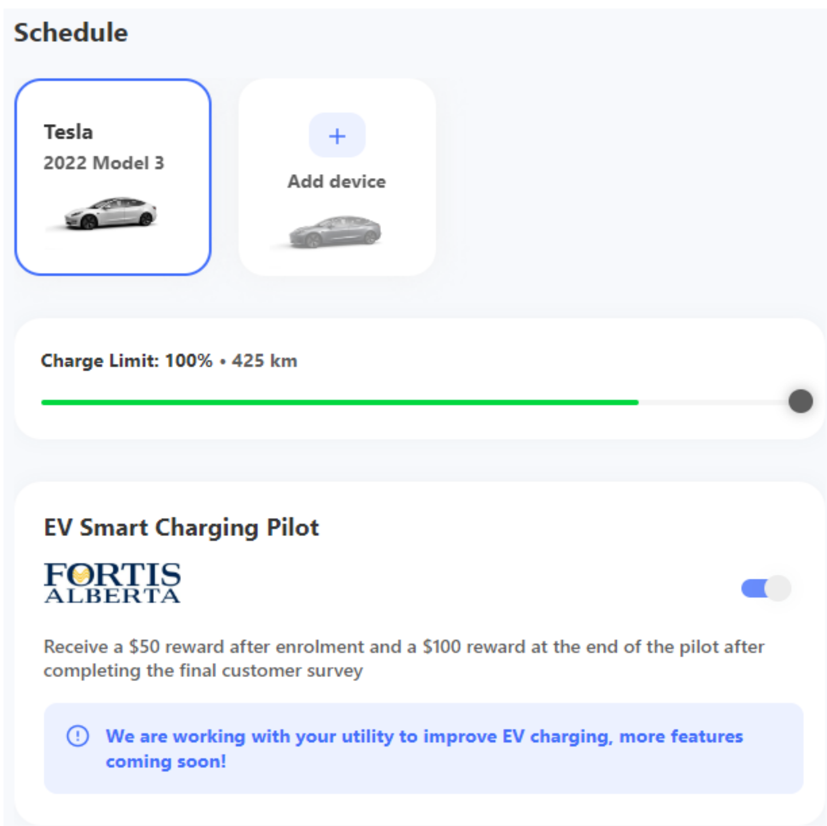
Appendices

A Treatment Messaging

This appendix details the communication and in-app experience for each group at the beginning of the treatment (starting on July 5, 2023).

A.1 Control Group

Email Communications: No email correspondence was initiated with participants in the Control group after initial enrollment.
In-App Experience: The Control group participants continued to experience the baseline features of the application. EV owners in this group could only monitor their charging data and schedule their EV charge start time within the App. The Figure below illustrates their in-app experience.



A.2 Time-of-Use (TOU) Group

Email Communications: Participants in the TOU group were sent an email with the subject line "Action needed – earn additional rewards" and a preheader stating "You now earn an extra 3.5 cents/kWh on off-peak home charging in FortisAlberta's EV Smart Charging Pilot." The users observed the information provided in the Figure below upon opening the email.

optiwatt

View Dashboard

Sign Up | Add Home | Add EV | Add Utility

PROGRAM UPDATE!

Please take action to earn more rewards

Congratulations, you have been selected to receive an additional benefit during our FortisAlberta pilot program!

What You Get

3.5 cents for every kWh charged off-peak at home

When You Get It

Beginning July 5, 2023, off-peak hours are defined as:
10 AM - 2 PM
10 PM - 6 AM

What You Should Do

Schedule your home charging to take place off-peak

Perks of this pilot update:

Lower Electricity Bills

You can now save up to $28/month by charging your EV off-peak

Smaller Carbon Footprint

By charging during off-peak hours, you're helping reduce CO2 emissions

Grid Support

Your EV is helping to contribute to overall grid stability and reliability

Frequently Asked Questions

How do I earn more rewards?	Starting 7/5/23, you will earn 3.5 cents/kWh on all off-peak home charging, up to 800 kWh per month per vehicle. This is in addition to your $50 sign-up and $100 program completion rewards.
How do I schedule my EV to charge off-peak?	You may use all available options, including but not limited to: your EV app, Optiwatt, or other 3rd party tools

View Your Dashboard

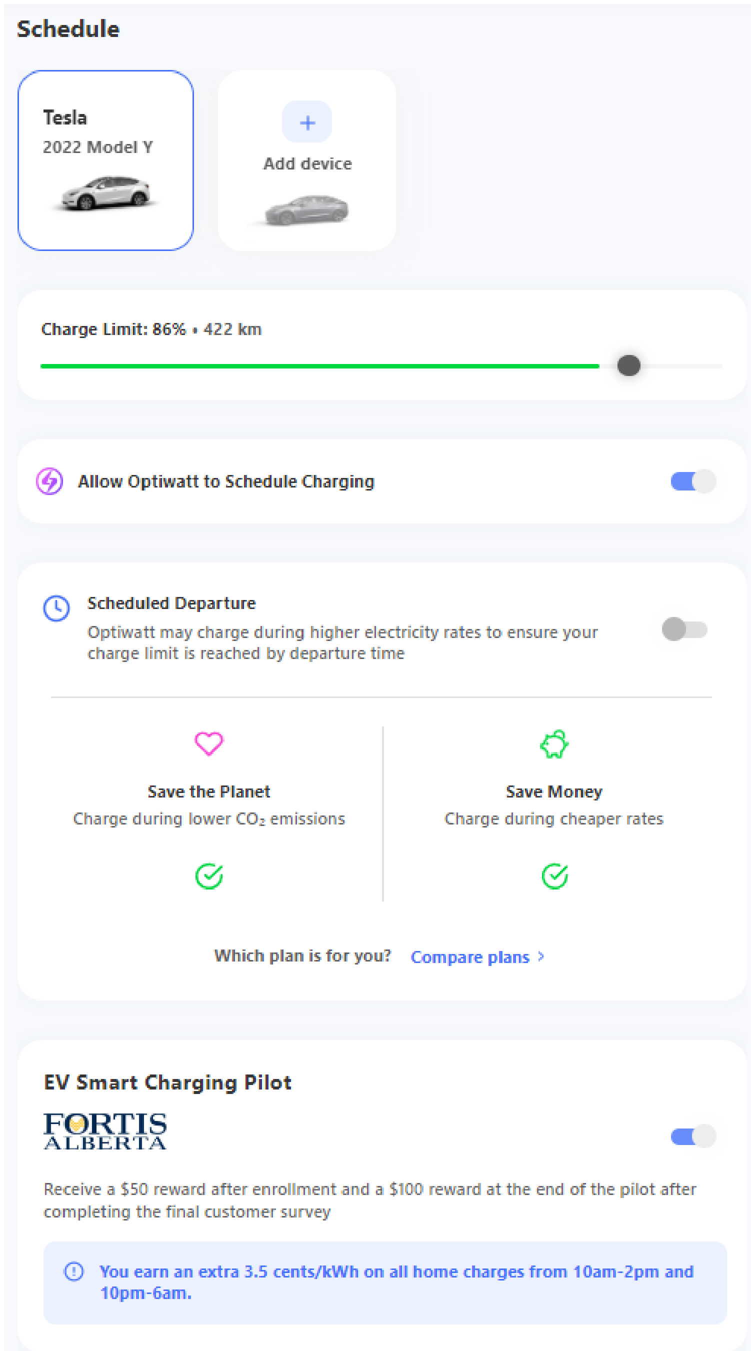
View the full FAQ

optiwatt

HOME | NEWS | FAQS

1540 Market St San Francisco, California 94102

In-App Experience: Within the application, this group encountered new messaging explaining the adjusted TOU rate structure in the program card. Additionally, these participants were granted access to activate or deactivate any Optiwatt scheduling functionalities, a feature unavailable during the initial phase of our field experiment.



A.3 Managed Group

Email Communications: Participants in the Managed group received the following email with the subject "Action needed – earn additional rewards" and a preheader that read "You now earn an extra 3.5 cents/kWh on all home charging in FortisAlberta's EV Smart Charging Pilot." The users observed the information provided in the Figure below upon opening the email.

optiwatt

Set Departure Times

Sign Up | Add Home | Add EV | Add Utility

PROGRAM UPDATE!

Please take action to earn more rewards

Congratulations, you have been selected to receive an additional benefit during our FortisAlberta pilot program!

What You Get

3.5 cents for every kWh charged at home

What Will Happen

Beginning July 5, 2023, Optiwatt will occasionally adjust your car's charging to accommodate the needs of the grid

What You Should Do

Set up Scheduled Departure in the Optiwatt app, to ensure your car reaches your battery target by your departure time

To charge urgently, opt out in the Charge Forecast of the Home tab, but lose that day's extra 3.5 cents/kWh reward

Perks of this pilot update:

Lower Electricity Bills
You can now save up to $28/month by shifting your charging schedule

Smaller Carbon Footprint
By charging during off-peak hours, you're helping reduce CO2 emissions

Grid Support
Your EV is helping to contribute to overall grid stability and reliability

Frequently Asked Questions

How will my charging behaviour change?	If you previously scheduled your charging in another app, or didn't schedule your charging at all, Optiwatt will alter your schedule. But rest assured, Scheduled Departure will ensure your range needs are always met.
How do I set up Scheduled Departure in Optiwatt?	Click the button below, or navigate to the Optiwatt app. In the Charging tab, you will see the option to set a Scheduled Departure time for each day of the week. We ensure your EV will reach your Charge Limit by that time each day.

Set Departure Times

View the full FAQ

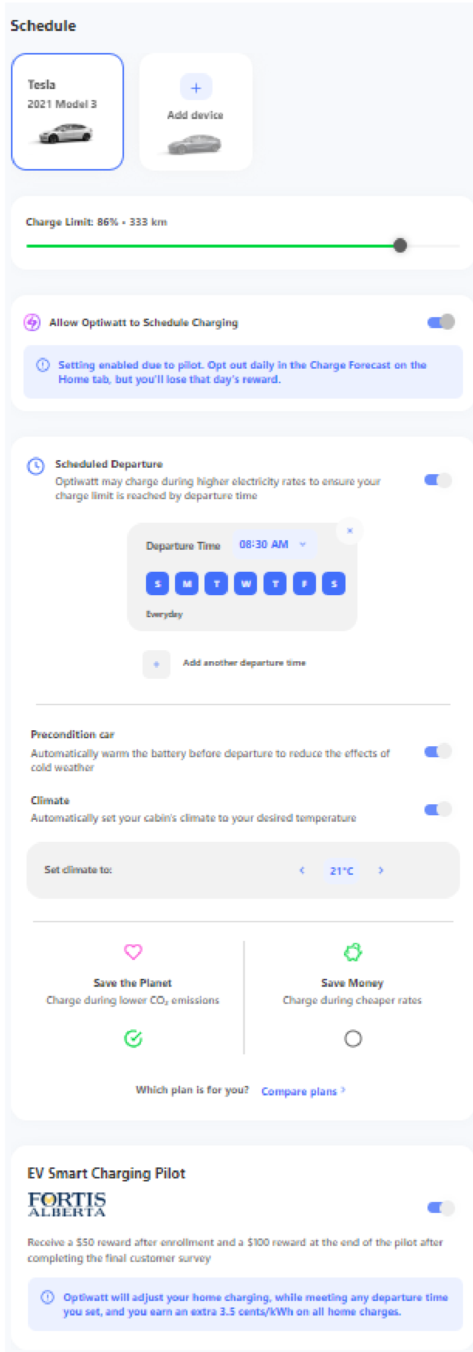
optiwatt

HOME | NEWS | FAQS

1540 Market St San Francisco, California 94102

No longer want to receive these emails? Unsubscribe.

In-App Experience: This group was presented with augmented messaging within the application, detailing the new incentive and scheduling parameters. The participants in the Managed group were not permitted to disable the Optiwatt scheduling feature, which was enabled to allow managed charging. They were encouraged, though not mandated, to use the Scheduled Departure functionality through notification. If Scheduled Departure was not enabled for a participant, a default time of 8:30 AM was applied to all weekdays.


Schedule
Tesla
2021 Model 3
Add device
Charge Limit: 86% • 333 km
Allow Optiwatt to Schedule Charging
Setting enabled due to pilot. Opt out daily in the Charge Forecast on the Home tab, but you'll lose that day's reward.
Scheduled Departure
Optiwatt may charge during higher electricity rates to ensure your charge limit is reached by departure time
Departure Time
08:30 AM
S M T W T F S
Everyday
Add another departure time
Precondition car
Automatically warm the battery before departure to reduce the effects of cold weather
Climate
Automatically set your cabin's climate to your desired temperature
Set climate to:
21°C
Save the Planet
Charge during lower CO₂ emissions
Save Money
Charge during cheaper rates
Which plan is for you?
Compare plans
EV Smart Charging Pilot
FORTIS ALBERTA
Receive a $50 reward after enrollment and a $100 reward at the end of the pilot after completing the final customer survey
Optiwatt will adjust your home charging, while meeting any departure time you set, and you earn an extra 3.5 cents/kWh on all home charges.

B Attrition

In this appendix, we describe the degree of attrition and explore whether sample attrition could be driving the conclusions we draw in the paper. At the start of the experiment, we randomly assigned 70 cars to the Managed group, 70 to the TOU group, and 62 to the Control group. However, 20 EVs dropped from the Managed group during the post-treatment period. Approximately half of these vehicles, nine in total, lost connection with the Optiwatt App due to "user password errors," likely caused by a technical issue accessing Tesla's API. User password errors only occurred in Tesla cars and disproportionately affected cars in the Managed group. Throughout most of the experiment (July-October 2023), Tesla did not support third-party API connections. Optiwatt described the password connection issue as one that arose when their software couldn't reach Tesla's system and then after a certain number of tries, it locked the users out and prompted a password reset. Users then needed to reset their passwords in both systems to re-establish the connection, but some did not complete this extra step.

Attrition in the other two groups included 9 EVs from the TOU group, none due to user password errors, and 3 EVs from the Control group, with one due to a user password error. If we compare attrition rates excluding user password errors, there is no statistically significant difference between the TOU and Managed groups, though both have higher attrition rates than the Control group.

The concern with attrition is that drivers who left the experiment might have had different charging behavior and/or different responses to the treatments than those who stayed, potentially affecting the magnitude of the calculated treatment effects. We assess this issue in several ways.

First, Table B1 compares the pre- and post-treatment charging characteristics of cars that completed the experiment with those that dropped out. For the pre-treatment comparison, we used data from the full pre-treatment period. The table shows that the two groups are statistically indistinguishable. This indicates that drivers who left the experiment did not require more total charging, nor did they differ significantly in how much they charged at home or during peak hours. For the post-treatment comparison, we analyzed charging behavior during the first month of the post-treatment period (July), as this month provides the most post-treatment data for the cars that left the experiment at some time post-treatment. Here too the charging behavior of those who left and those who stayed is quite comparable. The total amount charged, the amount charged at home, and charging at peak times are all statistically indistinguishable between the two groups. This suggests that drivers who left the experiment were not responding differently to the treatment in terms of the amount and timing of charging relative to those who stayed, for the month of July.

Second, we examine treatment effects over time. If drivers who left the experiment had systematically different driving behavior or were differently responsive to treatment than those who stayed, we would expect to see effects either increasing or decreasing over time. Figure B.1 displays the estimated treatment effects for our Constraint Violations (in kWh) for the TOU and Managed groups in peak and off-peak periods. These treatment effects correspond to a variant of regression equation (3) in the main text, adjusted to estimate month-specific treatment effects which replace the indicator variable Post_d with a vector of month-specific indicator variables. Figure B.1 plots the respective coefficients for these interaction terms for months in the post-treatment period. The treatment effects are statistically indistinguishable over time, implying that the drivers who remained in the experiment responded similarly to the treatment as those who were there at the beginning.

Additionally, in Figure B.2 we show the results of a similar analysis as in Figure B.1, focusing on our Charged kWh dependent variable at the vehicle level. Here too the estimated treatment effects are statistically indistinguishable over time. Figures B.1 and B.2 therefore offer further evidence that attrition due to drivers with certain treatment effects or charging patterns disproportionately dropping out of the experiment is unlikely to be driving our results.

Third, we employ a robustness check where we replace the attritted EVs in our sample with a representative Control EV and rerun our analysis as if they had not left our sample. More specifically, for each vehicle that left the experiment (regardless of treatment group), we randomly assigned the charging behavior of an active Control vehicle for each day following its departure. We the re-estimated the results of our main specification. The results of this analysis are presented in Table B2. This analysis yields results that are consistent with our main findings. As expected, with the larger number of EVs leaving the experiment in the Managed group and the inclusion of unmanaged Control EVs in place of the attritted EVs, the estimated treatment effects for the Managed group are attenuated downward. For example, looking at Column (2), the reduction in peak constraint violations decreased to -0.6188 from -0.7201 in our main specification reported in Table 2. These results serve as a lower bound for the estimated treatment effects. Despite the reduction in the estimated effects, we continue to observe similar conclusions as in our main analysis. The Managed group continues to exhibit a significant difference in off-peak violations when compared to TOU.

Finally, as we describe in Section 5.2, in December 2023 we offered the 59 remaining control customers to opt-in to a managed charging program that runs for 6 months. 35 respondents completed the survey and 34 opted into the program. 6 out of 34 (18%) EVs that opted into the Managed program unenrolled. This rate of attrition is comparable to the level observed for those EVs that were automatically enrolled into our initial managed charging treatment. More specifically, 11 EVs actively unenrolled from the initial managed treatment. Removing the 9 EVs that had password errors in the Managed group and left the program (described above), this is an active unenrollment rate of 11 out of 61 (18%).

Table B1. Comparison of Pre-Treatment and Post-Treatment Characteristics: Compliers vs. Non-Compliers

	Pre-Treatment			Post-Treatment		
Variable	Completed	Left	t-test (p-value)	Completed	Left	t-test (p-value)
Home Share (%)	75.79	73.68	0.65	75.79	78.84	0.60
	(23.87)	(23.84)		(28.59)	(28.96)	
Charge Duration (Minutes)	244.86	260.34	0.61	244.58	229.42	0.62
	(161.65)	(156.46)		(173.14)	(144.41)	
Energy Charged (kWh)	21.70	25.15	0.16	21.64	21.61	0.99
	(9.43)	(13.10)		(11.00)	(12.26)	
Max kW Charge (Power)	6.65	7.11	0.45	6.99	8.60	0.06
	(2.36)	(3.26)		(3.14)	(4.15)	
Off-Peak Share (%)	50.55	47.76	0.39	55.54	54.61	0.84
	(18.52)	(16.20)		(20.75)	(22.45)	
Off-Peak Share (%) - Home Only	52.36	49.02	0.41	58.89	59.10	0.96
	(21.60)	(20.45)		(24.42)	(23.12)	
Tesla (%)	85.29	84.38	0.89	85.29	84.38	0.89
	(35.52)	(36.89)		(35.52)	(36.89)	
Number of EVs	170	32		170	32	

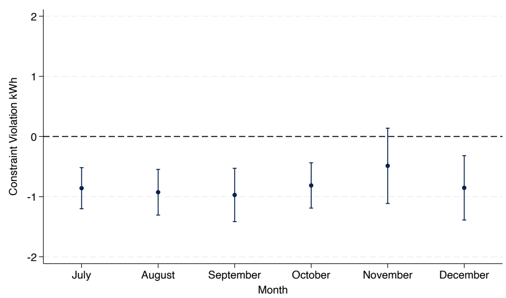
Notes. This table compares pre-treatment and post-treatment (during month of July) average values of various charging variables at the vehicle level separated by EVs that completed the experiment and those that left. Parentheses contain the standard deviations. Home Share represents the percentage of total charging kWh at home, Charge Duration is the daily number of minutes the EV is charged at home, Energy Charged is the kWh charged per day at home, Max KW Charge is maximum power of charge used per day at home, Off-Peak Share is the percentage of kWh charged in the off-peak either at home or away, and Off-Peak Share - Home Only is the percentage of kWh charged in the off-peak at home only. Tesla is the percentage of EVs that are Tesla and Number of EVs is the count of EVs. ANOVA (p-value) reports the p-value from one-way ANOVA tests for differences in means across groups.

Table B2. Estimated Treatment Effects by Group - Attrition Robust

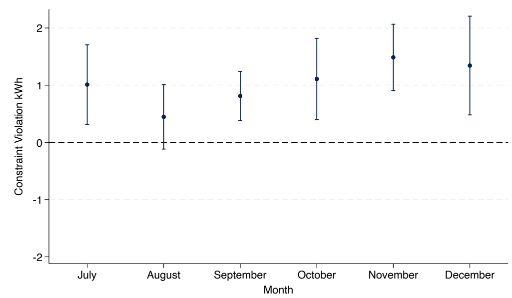
Group	Hours	(1) Charge kWh	(2) Constraint Violations
TOU	Peak	-0.187	-0.749
		(0.039)	(0.174)
	Off-Peak	0.227	0.965
		(0.046)	(0.276)
Managed	Peak	-0.051	-0.619
		(0.029)	(0.195)
	Off-Peak	0.052	-0.083
		(0.040)	(0.101)
Treatment Effect Comparison			
TOU - Managed	Peak	-0.136	-0.130
		[0.001]	[0.594]
	Off-Peak	0.175	1.047
		[0.000]	[0.001]
Observations		1,201,026	127,512

Notes. This table provides the estimated treatment effects for the EV-level dependent variable Charge kWh and the transformer-level dependent variable Constraint Violations (in kWh), using at-home charging only. The estimated treatment effects are separated into Peak and Off-Peak hours. Treatment Effect Comparison compares the treatment effects for TOU and Managed by Peak and Off-Peak, with p-values reported in the brackets for the Wald tests assessing the null hypothesis that the estimated treatment effects for TOU and Managed are equal. All specifications include fixed effects at the day-of-sample, and hour-of-day level. The Column (1) specification includes EV-level fixed effects while the Column (2) includes transformer-level fixed effects. Standard errors (in parentheses) in Column (1) are clustered at the transformer level for vehicles assigned to Managed and the EV-level for vehicles assigned to Control and TOU. Standard errors in Column (2) are clustered at the transformer level.

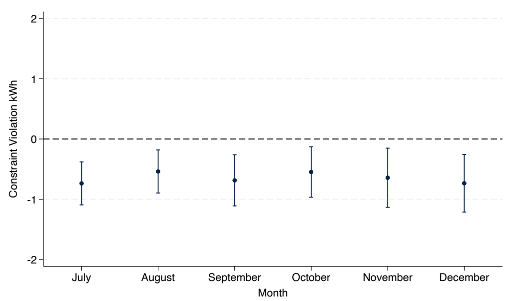
Figure B.1. Estimated Treatment Effects by Group and Month - Constraint Violations (kWh)



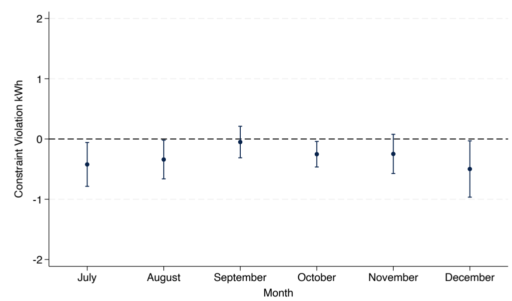
(a) TOU - Peak



(b) TOU - Off Peak



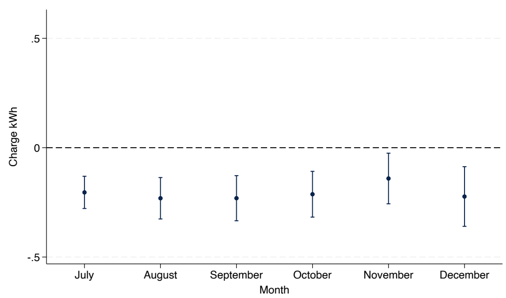
(c) Managed - Peak



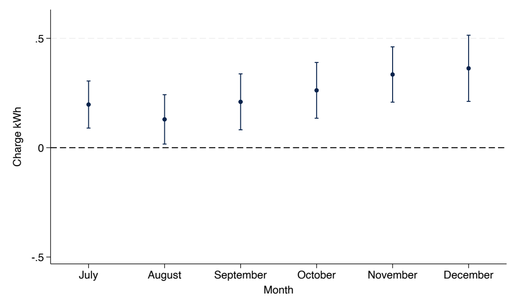
(d) Managed - Off Peak

Notes. Upper and lower bars represent the 95% confidence interval for each coefficient.

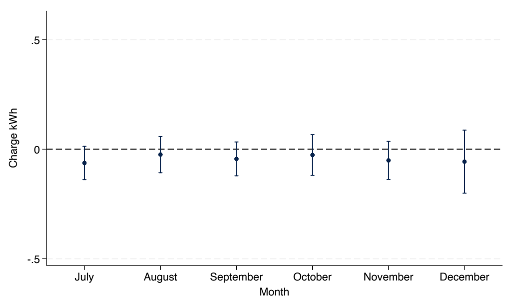
Figure B.2. Estimated Treatment Effects by Group and Month - Charged kWh



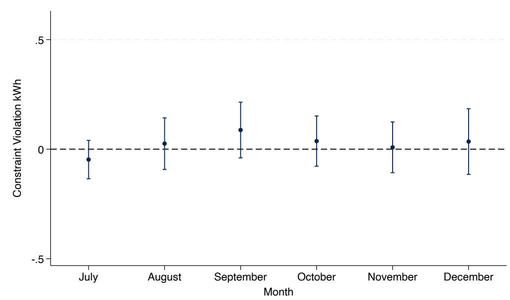
(a) TOU - Peak



(b) TOU - Off Peak



(c) Managed - Peak



(d) Managed - Off Peak

Notes. Upper and lower bars represent the 95% confidence interval.

C Supplementary Tables and Figures

C.1 Extensive Margin

In this section, we focus on data at the vehicle level to evaluate whether EV owners in the TOU or Managed groups differentially adjusted their daily frequency or quantity of charging kWh post-treatment, either at home only or in aggregate (i.e. at home and away charging). By looking at these cases separately, we can evaluate if there was a shift in the location of charging (e.g., from away to home charging) post-treatment for either group.

We estimate the following equation, using all vehicles in our sample, for each day d and vehicle i:

$$Y_{id} \;=\; \beta\, Post_d \times Group_i + \alpha_i + \tau_d + \eta_{id} \tag{4}$$

in which Y_{id} is one of two dependent variables: (1) a charging indicator variable if charging occurred on day d and (2) the Charge kWh is the summation of total charging kWh on day d. $Post_d$ is the post-treatment indicator that equals 1 starting on July 5, 2023, and 0 otherwise, $Group_i$ represents two indicator variables for the TOU and managed treatment groups. α_i is a vehicle-level fixed effect, τ_d is our day-of-sample fixed effect, and η_{id} is the error term. We cluster standard errors at the vehicle level.

We define a "day" between 9:00 AM and 8:59 AM the following day to capture the fact that EV owners systematically make their charging timing decisions in the afternoon/evenings. We consider two specifications where our dependent variables are constructed using at-home charging only and charging both at home and away.

Table C1 presents the results of our extensive margin analysis. We find no evidence of a significant change in charging frequency or charging kWh at the daily level for either treatment group relative to the Control, including at-home-only and both home and away charging. These results indicate that there is no evidence that EV owners responded to either treatment by shifting their charging location and/or aggregate charging patterns at the daily level differentially relative to the Control.

Table C1. Extensive Margin Analysis

	Charging Indicator		Charging kWh	
	Home-Only	Home and Away	Home-Only	Home and Away
TOU × Post	0.013	0.007	0.378	1.052
	(0.027)	(0.026)	(0.645)	(0.815)
Managed × Post	0.017	0.013	0.218	-0.206
	(0.026)	(0.026)	(0.659)	(0.843)
Observations	47,337	47,337	47,337	47,337

Notes. This table provides the estimated vehicle-level treatment effects for equation (4) for the dependent variables Charging Indicator and Charging kWh, using either at-home-only or both home and away charging. All specifications include fixed effects at the vehicle and day-of-sample level. Standard errors are clustered at the vehicle level. Statistical Significance $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

C.2 Comparison of EVs in Fortis' Territory to EVs in U.S. Metro Areas

In this Appendix, we compare driving and charging patterns in our sample to EVs in the United States. In particular, Optiwatt provided us with charging data from a randomized subsample of EVs in 14 major cities across the United States: Los Angeles, Sacramento, San Diego, San Francisco, San Jose, Las Vegas, Phoenix, Orlando, Miami, Chicago, Houston, San Antonio, Austin, and Seattle. These data cover the pre-treatment period in our sample (April 1, 2023 - July 4, 2023).

First, we focus on EVs in the US sample that were not on a TOU pricing program. This removes the 5 cities in California that are on default TOU programs and EVs in the remaining cities that reported to Optiwatt that they were on a TOU rate. This selection criteria is implemented to compare EVs that are on flat retail rates, as was the case in our Fortis sample pre-treatment.

Table C2 evaluates how our Fortis sample compares to the non-TOU US EVs sample, using data covering our pre-treatment period. This assessment of balance uses the same variables displayed in Table 1. While we do observe significant differences for a number of variables, the differences across the two samples are modest. EVs in the US sample charge more at home and a larger percentage in the off-peak. However, they are in comparable ranges. Further, the US sample has a higher proportion of Teslas, but both samples largely consist of Tesla EVs. We observe a comparable amount of daily energy charged at home and max power drawn from the chargers across the two samples. We take these results to demonstrate that while there are differences across the two samples, our Fortis EV sample is not an outlier compared to EV charging and driving behavior in large US cities.

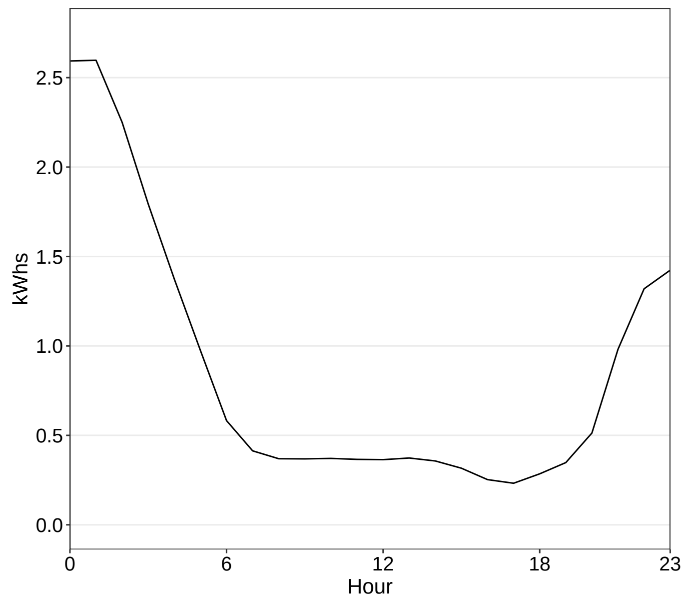
Table C2. Balance on Observable Characteristics by Sample Using Pre-Treatment Data

Variable	Fortis Sample	U.S. Sample	T-Test (p-value)
Home Share	75.46	83.74	.00
	(23.82)	(24.83)	
Charge Duration (Minutes)	247.31	279.11	.01
	(160.56)	(189.17)	
Energy Charged (kWh)	22.25	23.18	.21
	(10.14)	(8.93)	
Max KW Charge (Power)	6.72	6.80	.67
	(2.52)	(3.17)	
Off-Peak Share (%)	50.11	54.66	.00
	(18.17)	(20.13)	
Off-Peak Share (%) - Home Only	51.83	56.43	.00
	(21.41)	(22.05)	
Tesla (%)	85.15	98.49	.00
	(35.65)	(12.20)	
Number of EVs	202	1,985	

Notes. This table compares average values of various charging variables at the vehicle level between EVs in the Fortis' territory and 9 metropolitan areas across the United States: Las Vegas, Phoenix, Orlando, Miami, Chicago, Houston, San Antonio, Austin, and Seattle. The U.S. sample excludes EVs on Time-of-Use (TOU) plans and those that never charge at home, focusing on data from April 1, 2023, to July 4, 2023, the same period as the pre-treatment period for the Fortis sample. Parentheses contain the standard deviations. Home Share represents the percentage of total charging kWh at home, Charge Duration is the daily number of minutes the EV is charged at home, Energy Charged is the kWh charged per day at home, Max KW Charge is the maximum power of charge used per day at home, Off-Peak Share is the percentage of kWh charged in the off-peak either at home or away, and Off-Peak Share - Home Only is the percentage of kWh charged in the off-peak at home only. Tesla is the percentage of EVs that are Tesla and Number of EVs is the count of EVs. T-Test (p-value) reports the p-value from t-tests on the equality of means between the two groups.

Second, we are interested in evaluating how the US EVs that report being on a TOU rate in the Optiwatt sample charge their cars at home. Figure C.1 shows the average hourly charging kWh at home on days where charging occurs using all 14 major US cities provided by Optiwatt. For consistency, we focus on our pre-treatment sample period. These descriptive results are consistent with our main findings. EVs on TOU rates in the US sample have the highest average charged kWh arising in the evening off-peak period, with reduced charging in the evening peak. The largest charging kWh occur at midnight in the US sample. This is likely driven by the fact that many TOU rate structures have the lowest prices starting at midnight, as is the case in California's EV2 rate (Valdberg et al., 2022).

Figure C.1. Average Charged kWh by Hour in 14 U.S. cities



Notes. This figure presents the mean hourly charging kWh for EVs, including only days on which EVs incurred a positive charge at home, from 14 major cities across the United States: Los Angeles, Sacramento, San Diego, San Francisco, San Jose, Las Vegas, Phoenix, Orlando, Miami, Chicago, Houston, San Antonio, Austin, and Seattle. Data includes charging sessions between April 1, 2023, to July 4, 2023, the same period as the pre-treatment period for the Fortis sample. It only includes vehicles that self-report being on a TOU rate on the Optiwatt app.

C.3 Cluster Robustness

In this Appendix, we consider alternative levels of clustering for our standard errors. Table C3 presents the results for our Charge kWh dependent variable that is at the EV level. Column (1) clusters standard errors at the vehicle level, while column (2) clusters standard errors at the transformer level for vehicles assigned to Managed and the EV level for vehicles assigned to Control and TOU. The latter reflects the level of clustering from our main analysis. These results demonstrate that the standard errors and resulting statistical inference are highly robust to the level of clustering.

Table C4 presents results for our transformer-level dependent variable Constraint Violations (in kWh) with and without wild bootstrap robust standard errors. In our main analysis, for our transformer-level dependent variable Constraint Violations (in kWh), we cluster the standard errors at the transformer level resulting in 21 clusters. We implement the wild bootstrap approach detailed in Roodman et al. (2019) to evaluate the robustness of our results to having a relatively small number of clusters. Table C4 presents the results of our regression analysis with and without wild bootstrap clustered standard errors. Column (1) presents the results from our main analysis, while column (2) implements the wild bootstrap results. Comparing across the two columns, we observe a slight increase in the p-values (in parentheses) that evaluate if the individual treatment effects are statistically significantly different from zero and a corresponding widening of the 95% confidence intervals (in brackets). However, the statistical inference that we draw from our analysis is robust.

Table C3. Estimated Treatment Effects by Group - Charge kWh with Alternative Clustering

		(1)	(2)
Group	Hours	Charge kWh	Charge kWh
TOU	Peak	-0.203	-0.203
		(0.041)	(0.041)
	Off-Peak	0.229	0.229
		(0.047)	(0.047)
Managed	Peak	-0.048	-0.048
		(0.034)	(0.029)
	Off-Peak	0.062	0.062
		(0.040)	(0.040)
Treatment Effect Comparison			
TOU - Managed	Peak	-0.155	-0.155
		[0.000]	[0.000]
	Off-Peak	0.167	0.167
		[0.001]	[0.001]
Observations		1,131,426	1,131,426

Notes. This table provides the estimated treatment effects for the EV-level dependent variable Charge kWh, using at-home charging only. Column (1) clusters standard errors at the vehicle level, while column (2) clusters standard errors at the transformer level for vehicles assigned to Managed and the EV level for vehicles assigned to Control and TOU. The estimated treatment effects are separated into Peak and Off-Peak hours. Treatment Effect Comparison compares the treatment effects for TOU and Managed by Peak and Off-Peak, with p-values reported in the brackets for the Wald tests assessing the null hypothesis that the estimated treatment effects for TOU and Managed are equal. All specifications include fixed effects at the vehicle, day-of-sample, and hour-of-day level.

Table C4. Estimated Treatment Effects by Group - Constraint Violation with Wild Bootstrap Cluster Robust Standard Errors

Group	Hours	(1) Constraint Violations	(2) Constraint Violations
TOU	Peak	-0.772	-0.772
		(0.000)	(0.002)
		[-1.134, -0.410]	[-1.182, -0.349]
	Off-Peak	0.961	0.961
		(0.002)	(0.007)
		[0.384, 1.538]	[0.305, 1.620]
Managed	Peak	-0.720	-0.720
		(0.001)	(0.001)
		[-1.087, -0.353]	[-1.147, -0.307]
	Off-Peak	-0.146	-0.146
		(0.145)	(0.176)
		[-0.348, 0.055]	[-0.370, 0.076]
Treatment Effect Comparison			
TOU - Managed	Peak	-0.052	-0.052
		(0.826)	(0.824)
		[-0.534, 0.431]	[-0.567, 0.470]
	Off-Peak	1.108	1.108
		(0.001)	(0.003)
		[0.543, 1.673]	[0.469, 1.777]
Observations		127,512	127,512

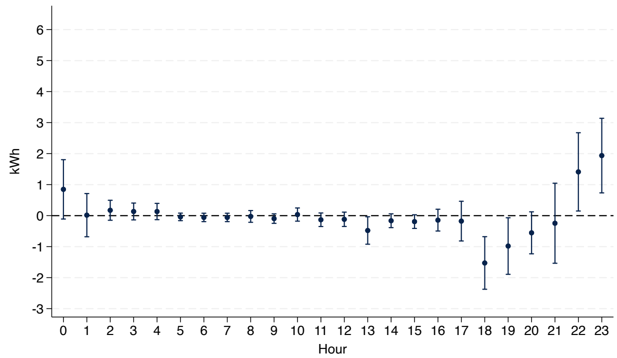
Notes. This table provides the estimated treatment effects for the transformer-level dependent variable Constraint Violations (in kWh), using at-home charging only. The estimated treatment effects are separated into Peak and Off-Peak hours. Column (1) presents the results from our main analysis with clustered standard errors at the transformer level. Column (2) clusters standard errors at the transformer level, but implements the wild cluster bootstrap detailed in Roodman et al. (2019). p-values are reported in parentheses and confidence intervals are provided in brackets. Treatment Effect Comparison compares the treatment effects for TOU and Managed by Peak and Off-Peak, with p-values reported in the parentheses and confidence intervals are provided in brackets for the Wald tests assessing the null hypothesis that the estimated treatment effects for TOU and Managed are equal. All specifications include fixed effects at the transformer, day-of-sample, and hour-of-day level.

C.4 Constraint Violation Estimates by Constraint Level

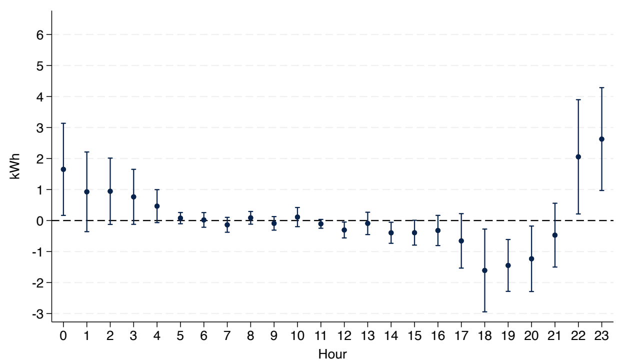
In this Appendix, we estimate the hour-specific treatment effects for the Constraint Violation dependent variable, allowing for differential treatment effects by the level of the randomly assigned transformer constraint. We consider three constraint categories: (i) Slack with a capacity limit between 20 - 24 kW, (ii) Moderate with capacity limits 16 - 19 kW, and (iii) Tight with capacity limits 12 - 15 kW. We run our hour-specific constraint violation regression described in Section 5.1 separately for each constraint Category.

Figures C.2 and C.3 present the estimated treatment effects for the TOU and Managed groups, respectively. The results are consistent with those in our main specification shown in Figure 3. For the TOU group with slack constraints, while more muted, the pattern of reduced peak period violations and elevated evening off-peak constraint violations persists. These effects increase in magnitude as the virtual transformer constraint becomes tighter leading to more severe violations in the off-peak hours. For the Managed group, the point estimates show a systematic reduction in constraint violations in the evening hours without a corresponding increase in the off-peak period. The magnitude of the reduction in constraint violations increases as the constraints become tighter. This is consistent with the expectation that the pressure on distribution transformers increases as the capacity constraint becomes tighter relative to the underlying non-EV electricity demand.

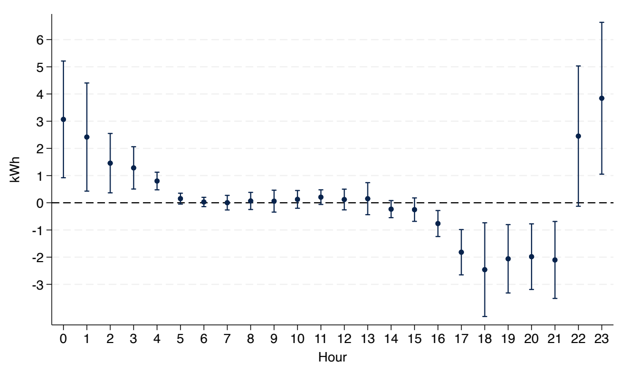
Figure C.2. Estimated Hourly Constraint Violation Treatment Effects by Constraint Category - TOU Group



(a) Slack



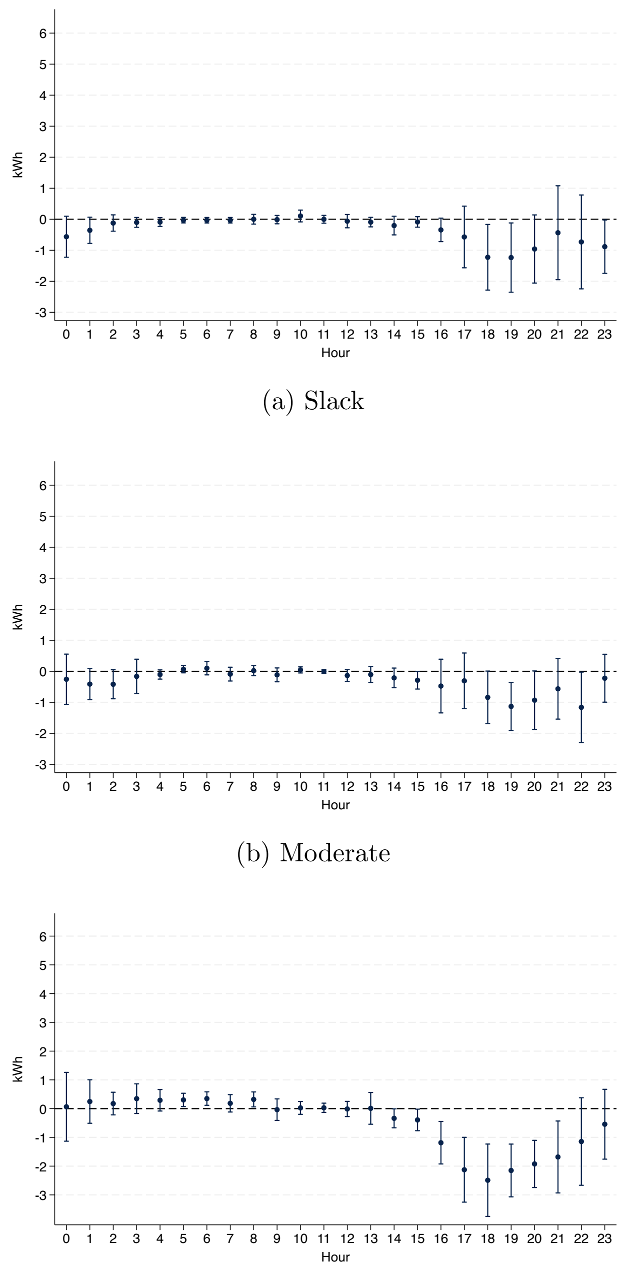
(b) Moderate



(c) Tight

Notes. Upper and lower bars represent the 95% confidence interval.

Figure C.3. Estimated Hourly Constraint Violation Treatment Effects by Constraint Category - Managed Group



(a) Slack

(b) Moderate

(c) Tight

Notes. Upper and lower bars represent the 95% confidence interval.

C.5 Alternative Transformer Grouping

This Appendix considers the effects of alternative transformer groupings for the Control and TOU EVs on our outcome of interest. Specifically, it explores aggregating vehicles based on similar charging habits and EV characteristics, in contrast to the random aggregation approach employed in the main analysis. In reality, EVs on a given transformer may be more homogeneous in their characteristics (and driving/charging habits) because of the observed geographical concentration of EVs (e.g., in high-income neighborhoods, commuting distances, etc.).

It is important to first note that the allocation of EVs in the TOU and Control groups to a specific transformer does not influence their charging behavior, as charging decisions are soley determined by the EV owners. This allows us to arbitrarily regroup these vehicles to examine the effects of different owner groupings on constraint violations. This is in contrast to the Managed group, in which the transformer headroom and the charging behavior of other EVs on the transformer affect charging times post-treatment through the managed charging algorithm.

We take two alternative approaches to group EVs into virtual transformers. First, we compute the average daily charged kWh at-home in off-peak hours pre-treatment. This measure was chosen because it captures both the intensity of at-home charging (in kWhs) and the timing of when a household tends to charge at home. We then rank EVs in the Control and TOU groups separately by this measure and allocate EVs into 10-EV virtual transformers starting with the EVs with the highest value on this charging measure down to those with the lowest. This approach groups the high, medium, and low off-peak charging EVs together in separate virtual transformers. This grouping will be referred to as "Alternative 1".

Second, we use an adapted kmeans clustering approach using pre-treatment data to group EVs into 10-EV transformers based on several characteristics, including the average daily charged kWh at-home in off-peak hours, the percentage of charging kWhs at-home, the average daily duration of charging (in minutes), estimated EV battery range, and the maximum power of charge used per day at home. This grouping will be referred to as "Alternative 2".

Kmeans clustering is effective at partitioning the EVs in our sample into groups to minimize the within-cluster differences. However, it does not ensure that the groups are of equal size. As a result, we develop an iterative approach to capture features of kmeans clustering, while allocating EVs into groups of 10. We start the algorithm by clustering EVs in TOU and Control separately using k-means clustering with 7 groups (representing our target number of transformers). For clusters with 10 or more EVs, we calculate the sum of squared errors (SSE) for all EVs in the cluster. For each of these clusters, we select the 10 EVs with the lowest SSE to achieve the most similarity of EVs within the cluster. For the remaining EVs that are not allocated into these 10-EV transformer groups, we rerun the kmeans clustering algorithm and follow the same process of finding groups of 10 EVs. This process continues until we have 10-EV transformer groups for all EVs in the TOU and Control groups.

For both alternative transformer groupings, we assigned the randomized transformer-by-day capacity limits that were used in our experiment. These capacity limits are used to compute the hourly transformer constraint violations with these alternative transformer groups.

Figure C.4 presents the average hourly Constraint Violations (in kWh) for the TOU and Control groups using our baseline transformer grouping from our experiment and Alternative 1 transformers. For the Alternative 1 groups, we observe a modest increase in the average constraint violations for both the Control and TOU groups pre- and post-treatment, compared to our baseline grouping. This is consistent with the fact that, for a subset of the alternative transformers, we observe an increase in coincidental charging leading to more constraint violations, while for others we have groups of EVs with lower overall charging levels leading to lower constraint violations. On average, we observe a small increase in violations for both groups compared to our baseline grouping. We continue to observe similar Constraint Violations for the Control pre- and post-treatment, but a sizable increase for TOU post-treatment.

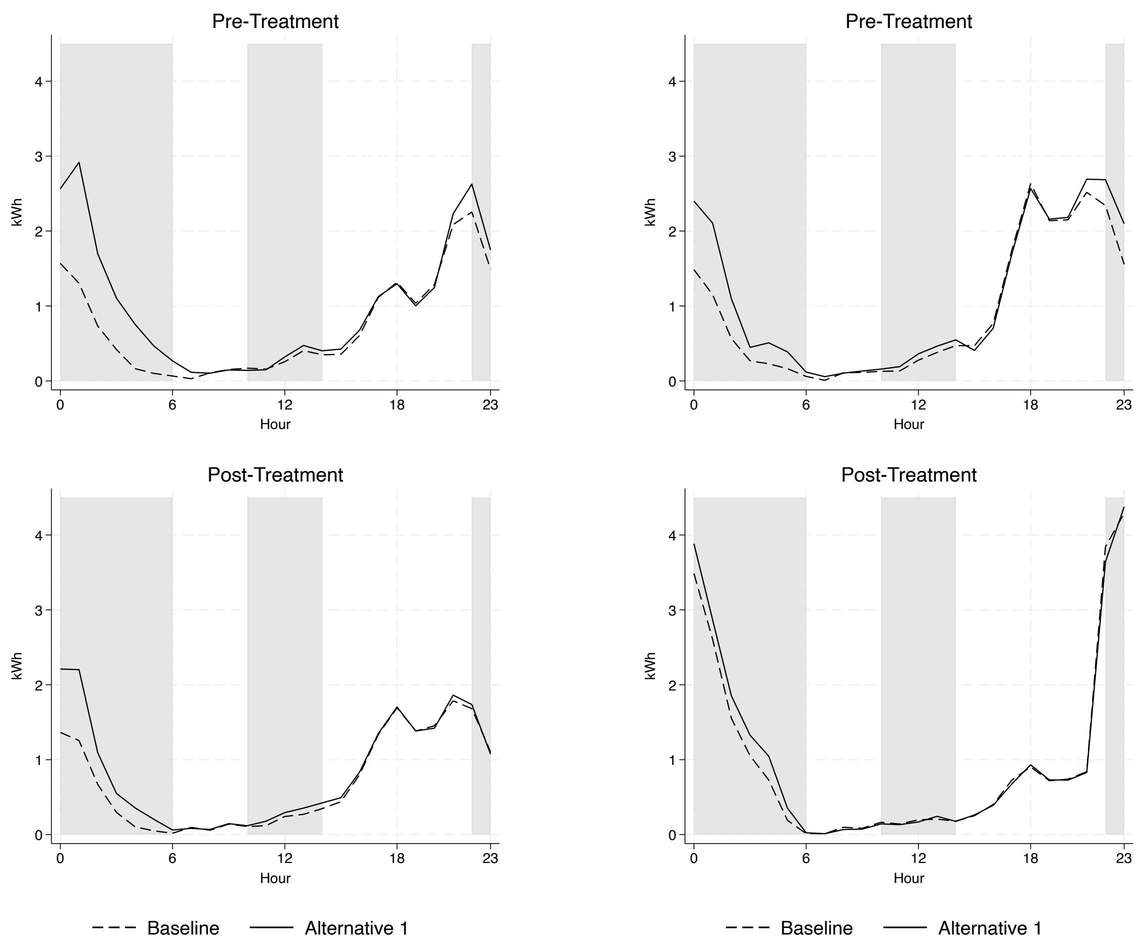
Figure C.5 presents the corresponding results using Alternative 2 transformer grouping. We do not observe a systematic increase in average constraint violations for either group. This is likely driven by the fact that we are using a wider array of characteristics to group EVs, leading to less homogeneity in coincidental charge timing within a transformer.

Table C5 presents regression results using the specification from our main analysis for the Constraint Violations dependent variable. We adjust our main specification by including only TOU and Control transformer groups to evaluate the impacts of the alternative groupings. Standard errors continue to be clustered at the transformer level. We use the wild bootstrap approach detailed in Roodman et al. (2019) for statistical inference to address concerns over having a small number of clusters. P-values are reported in parentheses and 95% confidence intervals are reported in brackets.

Column (1) provides estimated treatment effects for the TOU group using the transformer groupings from our experiment to serve as a baseline. Columns (2) and (3) present the estimated results with the two alternative transformer groupings. Despite having allocated EVs based on charging characteristics, we do not observe a large increase in the estimated treatment effects. In fact, the effects are reduced with the Alternative 2 transformers. These results could be driven by the fact that while we observe an increase in Constraint Violations for a subset of the alternative transformers due to more coincidental charging, for others we observe a reduction as we have a group of EVs that charge less often and/or have less charged kWh. In addition, for Alternative 1 we also observe a corresponding increase in the average Constraint Violations for the Control group both pre- and post-treatment, offsetting the increase in average TOU Constraint Violations.

These results suggest that while having more homogeneous EVs on a virtual transformer may increase Constraint Violations for certain transformers, it can reduce violations for others. More broadly, these results demonstrate that the key conclusions drawn from our analysis and sample are robust to alternative transformer groupings for the TOU and Control EVs.

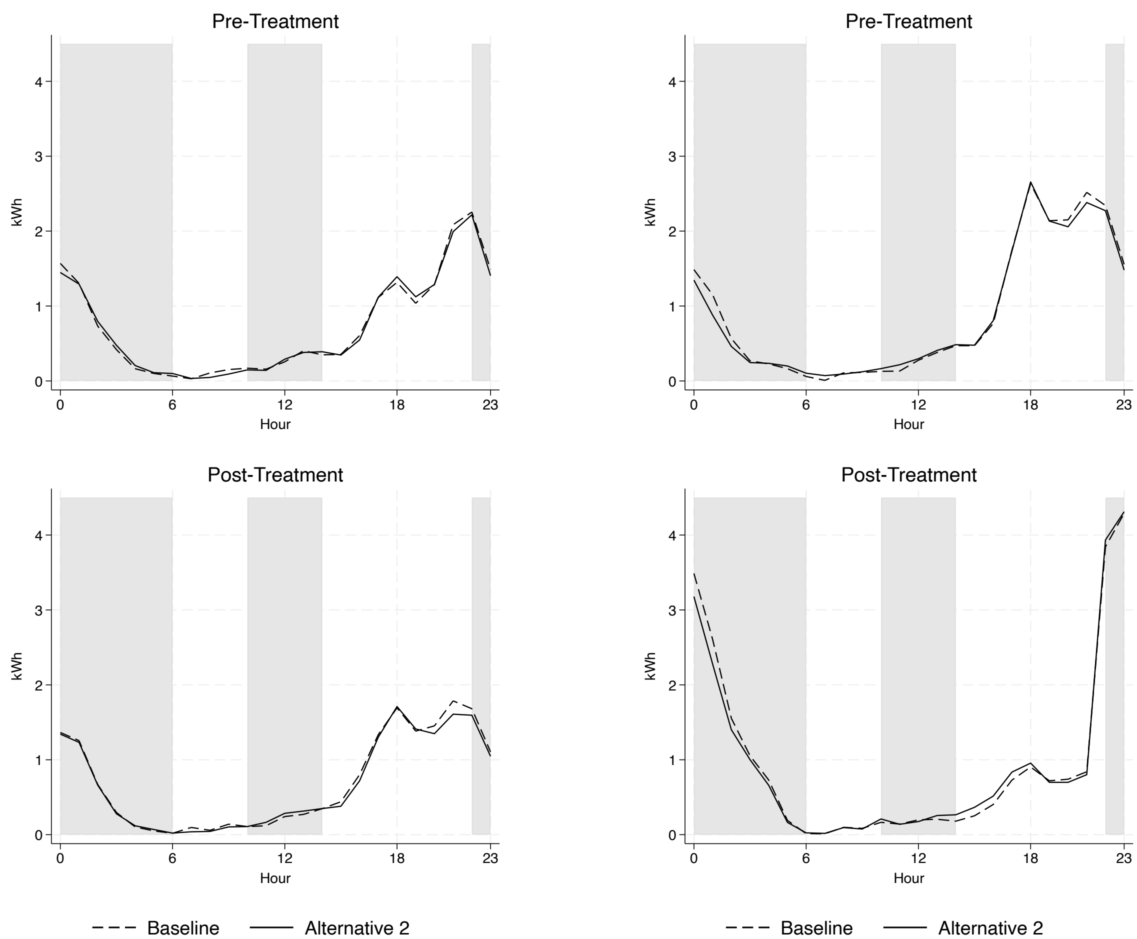
Figure C.4. Average Transformer Violations by Group and Hour - Baseline and Alternative Transformers 1



(a) Control (b) TOU

Notes. Average Transformer Violations represents the average magnitude of hourly distribution transformer constraint violations (in kWh) across all virtual transformers for the pre- and post-treatment periods. Baseline represents the virtual transformers from our main analysis, while Alternative 1 is alternative transformer grouping 1 which groups EVs based on their daily average charge kWhs in off-peak hours. The shaded areas represent our off-peak hours.

Figure C.5. Average Transformer Violations by Group and Hour - Baseline and Alternative Transformers 2



(a) Control (b) TOU

Notes. Average Transformer Violations represents the average magnitude of hourly distribution transformer constraint violations (in kWh) across all virtual transformers for the pre- and post-treatment periods. Baseline represents the virtual transformers from our main analysis, while Alternative 2 is alternative transformer grouping 2 which clusters EVs into groups of 10 based on their similarity across several charging and EV characteristics. The shaded areas represent our off-peak hours.

Table C5. Estimated Treatment Effects for the Alternative Transformer Grouping - Constraint Violation with Wild Bootstrap Cluster Robust Standard Errors

Group	Hours	(1) Baseline Transformers	(2) Alt. Transformers 1	(3) Alt. Transformers 2
TOU	Peak	-0.772	-0.772	-0.695
		(0.002)	(0.000)	(0.000)
		[-1.184, -0.355]	[-1.085, -0.452]	[-1.077, -0.333]
	Off-Peak	0.961	0.977	0.933
		(0.006)	(0.001)	(0.004)
		[0.302, 1.617]	[0.406, 1.559]	[0.338, 1.524]
Observations		85,008	85,008	85,008

Notes. This table provides the estimated treatment effects for the TOU group for the transformer-level dependent variable Constraint Violations (in kWh), using at-home charging only. The estimated treatment effects are separated into Peak and Off-Peak hours. The regression analysis only includes the TOU and Control transformers. Column (1) presents the results using the transformer groupings used in our main analysis, column (2) considers alternative transformer grouping 1 which groups EVs based on their daily average charge kWhs in off-peak hours, and column (3) considers alternative transformer grouping 2 which clusters EVs into groups of 10 based on their similarity across several charging and EV characteristics. Standard errors are clustered at the transformer level with the wild cluster bootstrap procedure detailed in Roodman et al. (2019). p-values are reported in parentheses and confidence intervals are provided in brackets. All specifications include fixed effects at the transformer, day-of-sample, and hour-of-day level.

C.6 Maximum Transformer Demand as the Number of EVs Vary

As the number of EVs on a transformer (N) increase, the maximum demand on the transformer is expected to increase due to periodic coincidental EV charging. However, heterogeneity in charging times across EV owners suggests that the growth in maximum demand should diminish as N increases. To quantify this relationship in our setting, we exploit the fact that EVs in the TOU and Control groups made their charging decisions independently of the virtual transformer assignments in our experiment. This independence enables us to construct counterfactual virtual transformers with varying EV allocations, allowing us to systematically analyze how the number of EVs on a transformer affects its maximum demand—an important input for transformer sizing decisions.

For both the Control and TOU groups, we randomly allocate EVs into virtual transformers of size N, where N varies from 2 to 10.[22] For each transformer, we calculate the maximum hourly demand that arises in the post-treatment period, where hourly demand consists of at-home EV charging from the N EVs on the transformer plus the representative non-EV residential load provided by Fortis. Then, for each treatment group, we compute the average of the maximum hourly demand for the post-treatment period across all of the virtual transformers. We repeat this process 100 times with different random allocations of EVs to new counterfactual virtual transformers of size N. We take the average across all 100 iterations to form an average post-treatment maximum demand on a virtual transformer with N EVs for the Control and TOU groups separately.

Figure C.6 presents the average maximum demand on the virtual transformers in the post-treatment period for the Control and TOU groups using the process outlined above. As expected, we observe an increase in the maximum transformer demand as the number of EVs increase, but it increases at a decreasing rate. The maximum demand on the virtual transformers for the TOU group lies above the Control group. This is consistent with our main findings that EVs in the TOU group systematically shifted their charging to the off-peak hours leading to a rise in the degree of coincidental charging post-treatment. Further, we see that while both groups' maximum demands are increasing at a decreasing rate, there is a divergence between TOU and Control as the number of EVs on the transformer increases. This

[22]In our experiment, we have 62 Control and 70 TOU EVs. For a certain N values, it was not possible to allocate all EVs to virtual transformers of size N. For example, when $N = 3$, we could only create 20 and 23 3-EV virtual transformer groups for the Control and TOU groups, respectively. The remaining EVs were dropped.

is also consistent with the higher degree of coincidental charging in the TOU group in the post-treatment period, leading the rate of the increase in the maximum demand to decline more slowly as N increases.

Figure C.6. Average Maximum Demand on Virtual Transformer by Number of EVs