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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 nearly a quarter of global carbon emissions (International Energy Agency, 2023). Consequently, the widespread adoption of electric vehicles (EVs) and the transition to a low-carbon electricity supply have become key climate mitigation strategies. Achieving widespread EV adoption, however, raises concerns about the ability of the existing electricity system to produce and deliver energy where and when it is demanded by EV owners.

Local distribution networks—the collection of poles, wires and transformers that connect consumers to the electricity system—are likely to be the earliest constraint on EV charging. Fast home EV chargers can consume power at rates up to ten times higher than typical household appliances, meaning that just a few EVs charging simultaneously can overload a distribution transformer, which generally serves fewer than a dozen homes.[1] This can cause the transformer to fail and/or accelerate the need for an upgrade.[2] Adding to this challenge is the fact that EV adoption tends to be geographically concentrated, meaning that even at low levels of utility-wide EV adoption, distribution transformer constraints can still be binding (Elmallah et al., 2022).

The scale of the required infrastructure turnover is massive. NREL (2024) estimates the current stock of distribution transformers to be 60 to 80 million units with a total capacity of 3 terawatts (TW) in the U.S. alone. NREL (2024) forecasts that a 160 to 260 percent increase in distribution transformer capacity by 2050 is necessary to accommodate the growth in end-use electrification, primarily due to EVs. Policies that reduce the need for distribution network investments, particularly distribution transformer upgrades, could significantly reduce the cost of electrifying the transportation sector.

One increasingly popular policy aimed at shifting the timing of EV charging and reducing strain on electricity systems is Time-of-Use (TOU) pricing, which sets a lower retail price during times of typically low system-wide demand (e.g. overnight or middle of the day in places with significant solar generation) and a higher retail price

[1] A level 2 (240V) EV charger typically draws power at a rate of 5 to 12 kilowatts (kW); other large residential appliances, such as air conditioners, clothes dryers, and ovens only use 1 to 4 kW.

[2] A distribution transformer steps down or up the voltage used in local distribution lines to the level used by customers. As (NREL, 2024) notes, "distribution transformers can facilitate loading of up to 200 percent of their nameplate capacity for brief periods of time, however, repeated and long-duration overloading will ultimately reduce the life of a transformer and raise the probability of the device failing."

in times of typically high system-wide demand (e.g. afternoon and early evening peak hours).[3] All told, over fifty distribution utilities across twenty-eight states currently offer a TOU EV rate (Alternative Fuels Data Center, 2024) to incentivize EV owners to charge their vehicles during off-peak times.

However, a potential unintended consequence of TOU pricing may arise due to the common financial incentive to charge during low-price hours. Given the observed flexibility of EV charge timing (Bailey et al., 2024) and the large size of the power draw from fast home chargers, this can result in coordination of charging into the narrow set of lowest-priced hours and, consequently, large "shadow demand peaks" of simultaneous charging on distribution transformers in areas with high levels of EV penetration.[4] As a result, TOU pricing risks accelerating the need for distribution transformer upgrades relative to a flat retail price where the price is constant across all hours (Turk et al., 2024).

Conversely, "managed charging" has the potential to reduce the need for distribution transformer upgrades relative to a flat retail price, while simultaneously being capable of mitigating system-wide generation costs.[5] Under managed charging, EV owners connect their vehicle(s) to their home charger and the distribution network operator controls the timing of charging of all connected EVs on the same distribution transformer. Vehicles are sequenced to avoid too many charging at once.

We employ a field experiment to quantify the impact of these two approaches—TOU pricing and managed charging—on transformer-level hourly demand and the magnitude of capacity violations under high EV penetration conditions. To simulate high EV penetration within a distribution network, we randomly assigned EVs into clusters of 10 vehicles, each served by a "virtual distribution transformer." For each transformer-day, the available headroom for EV charging was calculated as the difference between a randomly assigned transformer capacity and representative hourly non-EV demand. This virtual transformer method provides us with the unique opportunity to estimate the causal effects of TOU pricing and managed charging on charging coordination behavior within a group of vehicles, compared to a baseline of

[3] For example, Pacific Gas & Electric offers a TOU rate to EV owners in California ("EV2-A") of 31¢ per kilowatt-hour (kWh) during the "off-peak" hours of midnight to 3 p.m. and a higher price of either 62¢ (June to September) or 49¢ (rest of the year) during the "peak" hours of 4 to 9 p.m (PG&E, 2024).

[4] Most EVs come with Apps that enable owners to remotely schedule their charging. Many of these include features to prioritize charging into a location's cheaper TOU time periods, thus making it easier for coincident charging across EVs connected to the distribution transformer to occur.

[5] In our setting, we focus on avoiding distribution network capacity violations, but algorithms could readily incorporate optimization for generation costs.

flat pricing.

To conduct the experiment, we partnered with FortisAlberta, an electric distribution company in Alberta, Canada, and Optiwatt, a U.S.-based company that enables EV owners to schedule charging through their app. We recruited over 200 EV owners, primarily urban and suburban drivers, for our experimental pool. Their charging patterns, in terms of daily energy charged (kWh) and maximum charge power (kW), are similar to other North American EV owners.[6]

We randomly assigned EV owners to virtual transformers in each of three groups: (1) a TOU group, which was told they would receive 3.5 cents CAD/kWh for charging their electric vehicle at home during defined off-peak hours of the day; (2) a Managed group, which was told they would receive 3.5 cents CAD/kWh for all home EV charging while their EV's charging behavior was managed to avoid distribution transformer capacity violations; and (3) a control group, which remained on the utility's regular time-invariant rate and was not contacted after initial enrollment.[7]

We find the introduction of TOU pricing delivers, as intended, a considerable shift in EV charging kWh from peak to off-peak periods—a beneficial outcome for reducing system-wide electricity demand peaks. However, it also results in the unintentional coordination of EV charging in the cheaper overnight hours. We find the magnitude of transformer capacity violations more than doubles—exceeding the magnitude of violations in the peak period prior to the intervention—resulting in increased transformer capacity requirements and exacerbating strain on the existing distribution network. In contrast, managed charging successfully reduces the magnitude of capacity violations roughly in half, on average, across all hours of the day relative to the status quo flat rate. Furthermore, we find EV owners rarely opted out of managed charging, only overriding managed charging in approximately 1% of charge sessions.

Our empirical results demonstrate that an increasingly common retail pricing approach, Time-of-Use pricing, can have significant unintended consequences on distribution transformer capacity constraints with high penetration of electric vehicles. Simulation studies have considered the effect of TOU pricing concentrating EV charging into "off peak" hours using representative consumption curves (e.g., Turk et al., 2024; Elmallah et al., 2022; Muratori, 2018; Hilshey et al., 2012). By using a field experiment, we can directly observe consumer behavioral responses and, importantly, the resultant correlation of charging behavior. The use of virtual transformers al-

[6] Appendix C.2 compares charging behavior between our experimental sample and drivers in 9 major U.S. cities using the Optiwatt app.

[7] At the time of writing (August 2024), one Canadian dollar converts to roughly \$0.73 USD.

lows us to assess the impact of these two interventions—TOU pricing and managed charging—on distribution infrastructure under high EV penetration scenarios.

Our results point to a new challenge for demand-side flexibility in electrifying personal transportation and home heating and cooling: local distribution network capacity constraints. Existing literature primarily focuses on policies aimed at providing common price signals to consumers when electricity generation costs or system-wide demand are high (e.g., Harding and Sexton, 2017; Garnache et al., 2024). The distribution network challenge is more akin to a coordination challenge, requiring more granular time-varying and household-specific pricing solutions that are likely to face obstacles from consumers and regulators who might be averse to such complexity and implementation challenges. Instead, rather than focusing on price as signal, managed charging compensates consumers for providing a service—that of 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 under local distribution network limits.

Finally, our analysis speaks to the growing literature highlighting equity concerns arising from the energy transition. As higher-income households adopt new technologies, infrastructure costs often increase for lower-income non-adopters, as seen with solar panels (Borenstein, 2017) and the electrification of space and water heating (Davis and Hausman, 2022). Our work suggests similar dynamics for the transition to electric vehicles. Under existing cost allocation methodologies, EV-driven distribution transformer costs will be borne by all customers, not just EV adopters, which recent research finds are generally higher-income households (Gillingham et al., 2023). Our findings indicate that TOU pricing, a common retail rate design, could increase EV integration costs, potentially exacerbating the financial burdens for lower-income households.

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 constraint developed by Boiteux and Stasi (1964). Consider a distribution transformer, which must be sized sufficiently to meet the maximum aggregate peak demand of a 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.

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 (Eq. 1) 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 must the transformer 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 the correlation, K_i, of any individual's irregularity 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 the distribution transformer capacity requirement, 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 moreover level 2 chargers, significantly increase the potential irregularity of individual loads, σ_i, on account of 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, whose power draw can range from 5 to 12 kW, more than doubles the potential peak power draw, significantly increasing σ_i. The issue of increased correlation of irregularities is less clear with EV charging. By separating the energy demand (charging) from the electric vehicle's service (driving), it is not clear *ex-ante* that K_i needs to increase in a world with more EVs (Bailey et al., 2024). This is where TOU pricing may play an unintentional role in increasing the correlation of charging behavior (Turk et al., 2024). By creating a coordinating mechanism to target a narrow set of hours in cheap price 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 the correlation of charging behaviour.

3 Experimental Design and Data

The field experiment was conducted in partnership with FortisAlberta ("Fortis"), a distribution utility serving residents in Alberta, Canada, and Optiwatt, a U.S.-based company that connects consumers to their EVs through an app.[8] Residential households in Fortis' service territory face time-invariant retail rates that can vary at most monthly.

In early 2023, households with EVs in Fortis' territory were recruited to join the "EV Smart Charging Pilot" through various advertising methods, including social media. To participate, households voluntarily signed up for the program through the Optiwatt app. They received \$50 upon sign-up and \$100 upon completion at the end of 2023. While Optiwatt's app offers additional functionality, EV owners in our experiment could only monitor their charging data and schedule their EV charge start time through the app.

We recruited 202 EVs to take part in our experiment. The EVs are primarily located in suburban and urban regions near the two largest cities Edmonton and Calgary, with just 14% in areas classified as rural (Statistics Canada, 2024). Comparing participants' charging behavior with drivers in 9 major U.S. cities using the Optiwatt app, we find that they were fairly representative of current EV owners across North America.[9]

After monitoring their consumption for several months, we randomized EV owners into three treatment groups: (i) Control [62 EVs], (ii) TOU [70 EVs], and (iii)

[8] Fortis provides services to more than 60% of Alberta's electricity distribution network, serving over 600,000 end-users.

[9] The U.S. sample is plugged in for slightly longer (around 50 minutes more each day), but the mean daily energy charged in the experimental sample (22.3 kWh) is within 1 kWh of the U.S. sample (23.2 kWh). The maximum power drawn is also quite similar, 6.7 kW for the experimental sample and 6.8 kW for the U.S. sample, suggesting comparable grid demands. See Appendix C.2.

Managed [70 EVs] in July 2023.[10] Households assigned to the TOU and managed groups were defaulted into their treatment group and informed they would receive their respective incentives starting July 5, 2023, the start of our treatment period. For details on the messaging provided to participants, see Appendix A. The control group received no additional messaging and were simply monitored for the remainder of 2023.

Those assigned to the TOU group were notified they would receive a financial incentive of a 3.5¢/kWh reward (paid through the Optiwatt app) for all at-home charging that occurred during "off-peak" hours between 10am – 2pm and 10pm – 6am.[11] The 3.5¢/kWh reward is roughly a 19% reduction in the variable price. EV owners were encouraged to use the Optiwatt app to schedule their EV charging.

Participants in the managed group were informed they would receive 3.5¢/kWh for all home EV charging but that Optiwatt would occasionally adjust their charging times to meet grid needs. Optiwatt's managed charging algorithm ensures that EVs reach their pre-set charge targets by their stated "scheduled departure" time each day. Participants could opt out of managed charging and charge immediately by pressing a "Charge Now" override button in the Optiwatt app, but doing so would forfeit the 3.5¢/kWh reward that day.

To understand the potential impact of EV charging on the distribution network with a large number of EVs, we developed "virtual transformers." We randomly assigned households to seven 10-car virtual transformers for both managed and TOU groups, and six 10-car control transformers.[12]

Optiwatt passively monitored the charging behavior of EVs in the control and TOU groups. For the managed group, Optiwatt actively controlled charging. It ensured that all EVs plugged in at home reached their charge targets before their scheduled departure times, while sequencing charging amongst EVs in a transformer group to fit all charging within the virtual transformer's capacity throughout the day. Constraint violations were allowed to occur if the grid constraint was sufficiently tight that the plugged-in EVs could not all achieve their charge targets before their

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

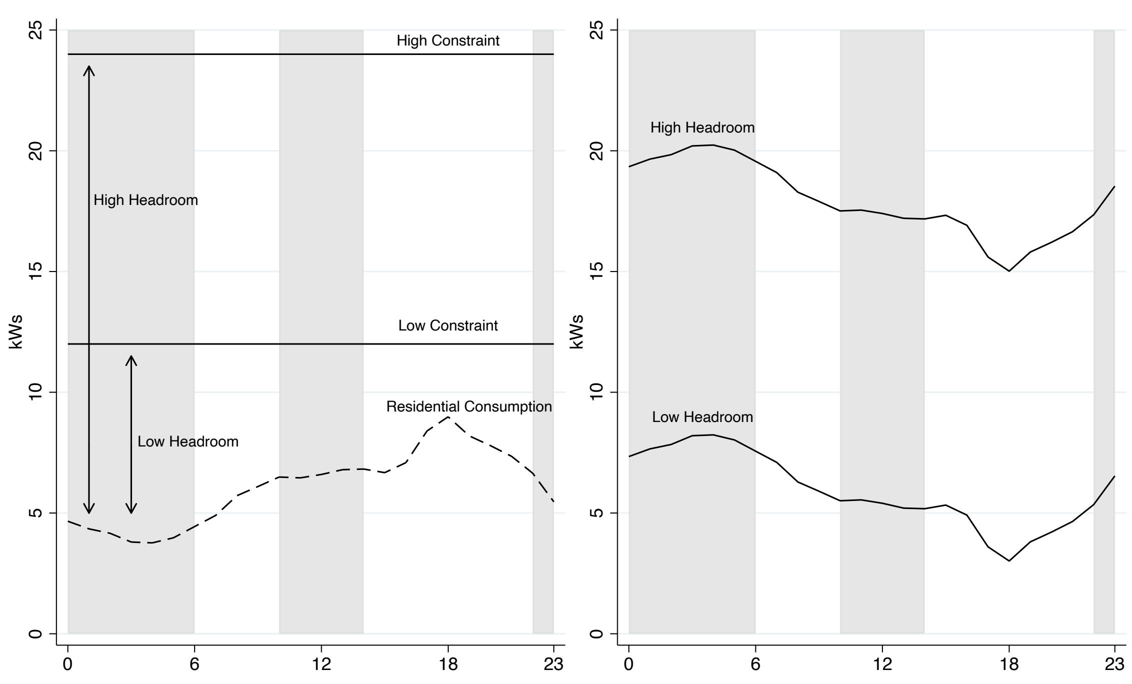
[11] The 3.5¢ off-peak to peak difference is a *conservative* difference relative to other common TOU rates. For example, the Canadian provinces of British Columbia and Ontario have off-peak to peak differences of 10¢ and 26¢, respectively.

[12] We end up with one additional virtual transformer with only 2 EVs (with its capacity adjusted accordingly). We undertake robustness checks excluding this group and our conclusions are unchanged.

departure times.

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. The left side of 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.

Figure 1. Illustration of Virtual Transformer Capacity



The daily transformer capacity limits were drawn from a distribution ranging from 12 to 24 kW.[13] These transformer capacity limits were empirically-grounded based on typical distribution transformer ratings (Hilshey et al., 2012; EnergyHub, 2023). The right side of Figure 1 shows the difference between the transformer capacity limits and the underlying residential household demand, indicating the range of available headroom for EV charging.[14] The least room is available in the evening peak, with more capacity available overnight and into the early morning hours.

[13]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 to increase statistical power.

[14]For virtual transformer groups with fewer than 10 cars, this charging headroom was proportionally scaled downward such that the per-EV distribution constraint was equivalent to the 10-EV transformers.

Randomizing the transformer capacity limits across a range of values helps address the limitation of using a single representative load profile for non-EV demand. In reality, individual non-EV load variability creates periods of slackness and tightness in charging headroom. Our range of constraint values captures this variability, creating scenarios where from one to three level 2 EV chargers can operate simultaneously.

Data and Assessment of Balance

Our study data span from April 1 to December 13, 2023.[15] We observe information on each charging session, including start and end times, kWh charged, charger power (kW), and location of charging (home or away). We also have information on the EV make, model, year, and battery range.

We compare average values of various EV charging metrics and vehicle characteristics across the three groups to evaluate if we have balance on observables, using pre-treatment data. Table 1 demonstrates that our treatment groups are well-balanced. Using a one-way ANOVA test, the table shows no statistically significant differences in the means of each variable across the three groups.[16]

Approximately 75% of all charged kWh occur at home, primarily on level 2 chargers averaging a maximum of 6-7 kW. The majority of EVs in our sample are Teslas. Around 50% of all kWh are charged during off-peak hours in the pre-treatment period. This highlights that while a significant portion of charging is already occurring in the off-peak times, before any incentives are provided, there remains a considerable margin of EV charging that could be shifted to off-peak hours.

4 Descriptive Statistics

We start with a descriptive analysis to examine changes in charging behavior across our three treatment groups. We then assess how these groups differ in their violations of virtual transformer constraints before and after exposure to financial incentives.

Figure 2a shows the mean hourly charging kWh per vehicle across our three groups

[15] Data collection concluded on December 13th, 2023, as participants received an offer on December 14th to join a subsequent program starting on January 1, 2024.

[16] During the experiment, 32 vehicles exited. In Appendix B, we compare observables between vehicles that dropped out and those that stayed in and do not find statistically distinguishable differences. We also document that attrition occurred slowly over time, not immediately in response to treatment. Finally, we estimate treatment effects over time and find that they do not change as vehicles dropped out.

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	

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.

before and after treatment, focusing on days with positive home charging.[17] The shaded areas indicate off-peak hours. Across all three groups, we observe similar charging profiles in the pre-period with higher mean charging kWh in the evening starting at 6pm and continuing overnight.

In the control group, we observe consistent behavior pre- and post-treatment. This reflects the absence of incentives for this group. In contrast, we see notable changes in the TOU group's charging patterns post-treatment. There is a considerable increase in charging kWh beginning at the start of the off-peak period and continuing through the night, and a reduction in the evening peak (i.e., 5pm to 10pm). This shift is consistent with a response to financial incentives for off-peak charging.

For the managed group, we observe only a modest reduction in peak hour charging and slightly more charging in the early morning off-peak hours. This pattern aligns

[17] A "day" spans from 9:00am-8:59am the following day, allowing for overnight charging decisions.

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. Therefore, to assess managed charging relative to TOU pricing in terms of distribution capacity requirements, we need to investigate the extent to which each group violates distribution transformer constraints.

Figure 2b summarizes the average hourly distribution transformer constraint violations (in kWh) by treatment group and the pre-and post-treatment periods. During pre-treatment, each group shows higher constraint violations in the evening, where 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. We see consistent patterns of constraint violations before and after treatment for the control group.

The TOU group displays a sharp increase in constraint violations post-treatment at the beginning of the off-peak period alongside a decrease during evening peak hours. The magnitude of the off-peak violations exceeds those in the peak period prior to treatment, demonstrating that TOU has the potential to accelerate the need for transformer upgrades.

In contrast, the managed group shows a consistent reduction in constraint violations post-treatment. Unlike the TOU group, they reduced peak violations without any corresponding increase in off-peak hours. This across-the-board reduction suggests that drivers allowed Optiwatt's managed charging algorithm to coordinate vehicle charging.

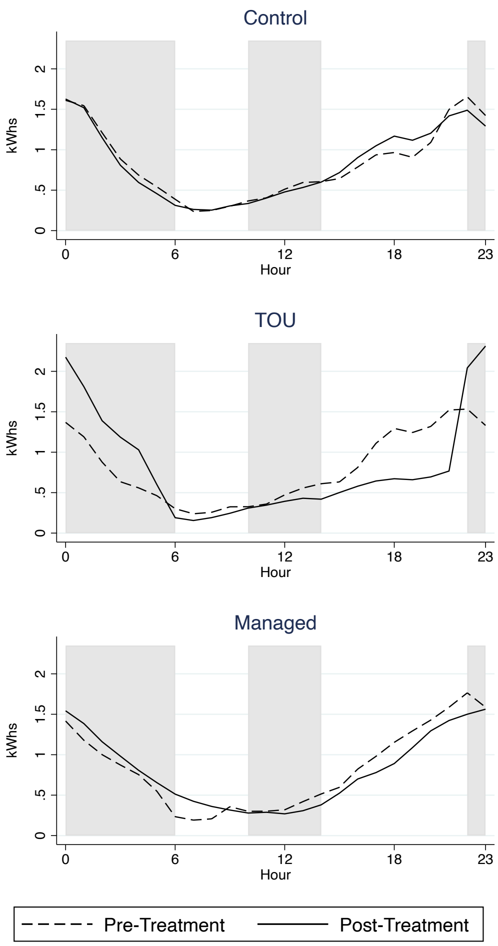
5 Empirical Strategy and Results

5.1 Charge Timing and Constraint Violations

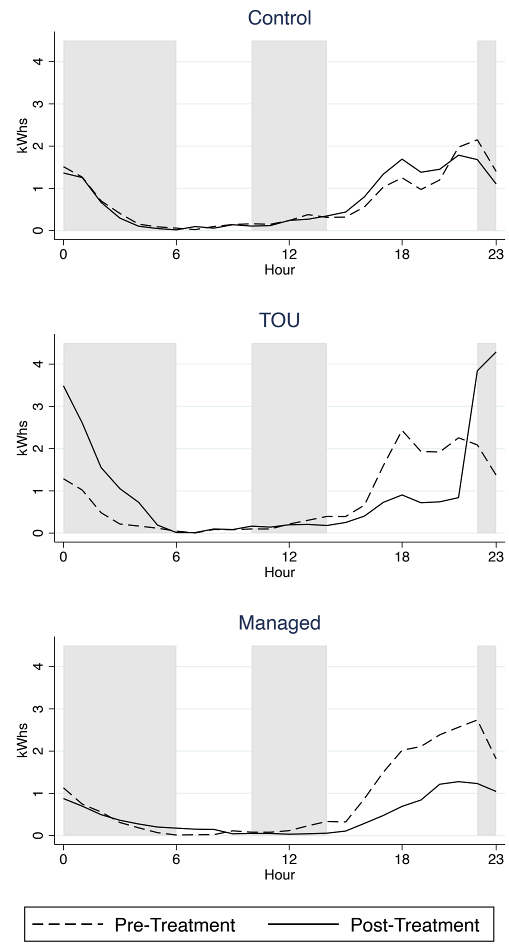
The descriptive evidence above suggests that treatment incentives impacted charging behavior and, subsequently, distribution transformer constraint violations. To rigorously test this, we employ a difference-in-difference (DID) estimation strategy. We aggregate hourly vehicle-level data to the distribution transformer, focusing exclusively on at home charging. This approach allows us to quantify how treatment incentives translated into changes in charged kWh and distribution transformer constraint violations.[18]

[18]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

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



(a) Average Charged kWh



(b) Average Transformer Violations

Notes. Average Charged kWh presents the mean hourly charging kWh including only days on which EVs incurred a positive charge at home and Average Transformer Violations represents the average magnitude of hourly distribution transformer constraint violations (in kWh) across all virtual transformers by treatment group for the pre- and post-treatment periods. The shaded areas represent our off-peak hours.

For each hour t and distribution transformer d, we estimate the following equation:

$$Y_{dt} = \beta_0 \,\text{Post}_t \times \text{Group}_d + \beta_1 \,\text{Post}_t \times \text{Group}_d \times \text{Off Peak}_t + \alpha_d + \tau_t + \epsilon_{dt} \quad (3)$$

where Y_{dt} represents one of our two dependent variables: (1) the magnitude of the distribution transformer constraint violations (in kWh) and (2) the EV electricity charged (in kWh) ("Charge kWh") that occurred on the distribution transformer. The dependent variable Charge kWh is normalized by the number of EVs on the virtual transformer, providing a measure of the total Charge kWh per EV on the transformer. Post_t is an indicator that equals 1 starting on July 5, 2023 (post-treatment) and 0 otherwise. Group_d consists of indicator variables for the TOU and managed treatment groups. We interact the $\text{Post}_t \times \text{Group}_d$ variable with an off-peak indicator variable, Off Peak_t, which equals 1 if hour t falls within our definition of off-peak hours. This specification allows us to assess the treatment's impact on peak and off-peak charging behaviors for both treatment groups.

We include fixed effects at the transformer level, α_d, to control for time-invariant transformer characteristics. τ_t denotes a vector of time fixed effects for the day-of-sample and hour-of-day. These fixed effects control for time-varying factors (e.g., seasonality) that may influence charging decisions. We cluster standard errors at the transformer level.

We extend the specification in (3) to interact the $\text{Post}_t \times \text{Group}_d$ variable with hour-specific indicators. This allows us to estimate how exposure to TOU and managed charging treatments impacted our dependent variables for each hour of the day.

Table 2 presents results from the transformer-level regressions. Focusing on the Charge kWh results in column (1), the TOU group shows a reduction in peak-hour charging, though statistically insignificant, and a large and statistically significant increase in off-peak charging. The off-peak coefficient represents a 62% increase relative to the pre-treatment mean TOU off-peak value.[19] In contrast, the managed charging group has no statistically significant coefficients. These results are consistent with the descriptive evidence in Figure 2a, where TOU shows a sizable shift to off-peak hours, while the managed group does not exhibit a distinct change in its hourly charging patterns.

Column (2) displays the impact of treatments on distribution transformer constraint violations. Both the TOU and managed charging groups have statistically

provides evidence that drivers did not shift charging locations post-treatment.

[19] This calculation reflects $0.2408/0.3886 \approx 0.62$.

Table 2. Estimated Transformer-Level Treatment Effects by Group

Group	Hours	(1) Charge kWh	(2) Constraint Violations
TOU	Peak	-0.0755	-0.5031
		(0.0580)	(0.1743)
	Off-Peak	0.2408	0.8297
		(0.0699)	(0.2990)
Managed	Peak	0.0103	-0.5062
		(0.0344)	(0.1370)
	Off-Peak	0.0498	-0.3062
		(0.0463)	(0.1048)
Mean Dep. Var. (Pre-Treatment)			
TOU	Peak	0.3898	0.9838
	Off-Peak	0.3886	0.6224
Managed	Peak	0.3982	1.0237
	Off-Peak	0.4431	0.6722

Notes. This table provides the estimated transformer-level treatment effects for equation (3) for the dependent variables Charge kWh and Constraint Violations (in kWh), using at-home charging only. The estimated treatment effects are separated into Peak and Off-Peak hours. The Mean Dep. Var. (Pre-Treatment) represents the mean value of each dependent variable between April 1, 2023 - July 4, 2023, separated into Peak and Off-Peak hours. All specifications include fixed effects at the transformer, day-of-sample, and hour-of-day level. Standard errors (in parentheses) are clustered at the transformer level.

significant reductions in peak-hour transformer constraint violations. These reductions amount to 51% and 49% of the pre-treatment average hourly peak values for the TOU and managed groups, respectively.[20] However, the TOU group exhibits a significant increase in off-peak constraint violations, up by 133% compared to the pre-treatment off-peak average value. In contrast, the managed charging group has a significant reduction in off-peak hour constraint violations kWh (i.e., a reduction of 46% relative to the pre-treatment off-peak average value).[21]

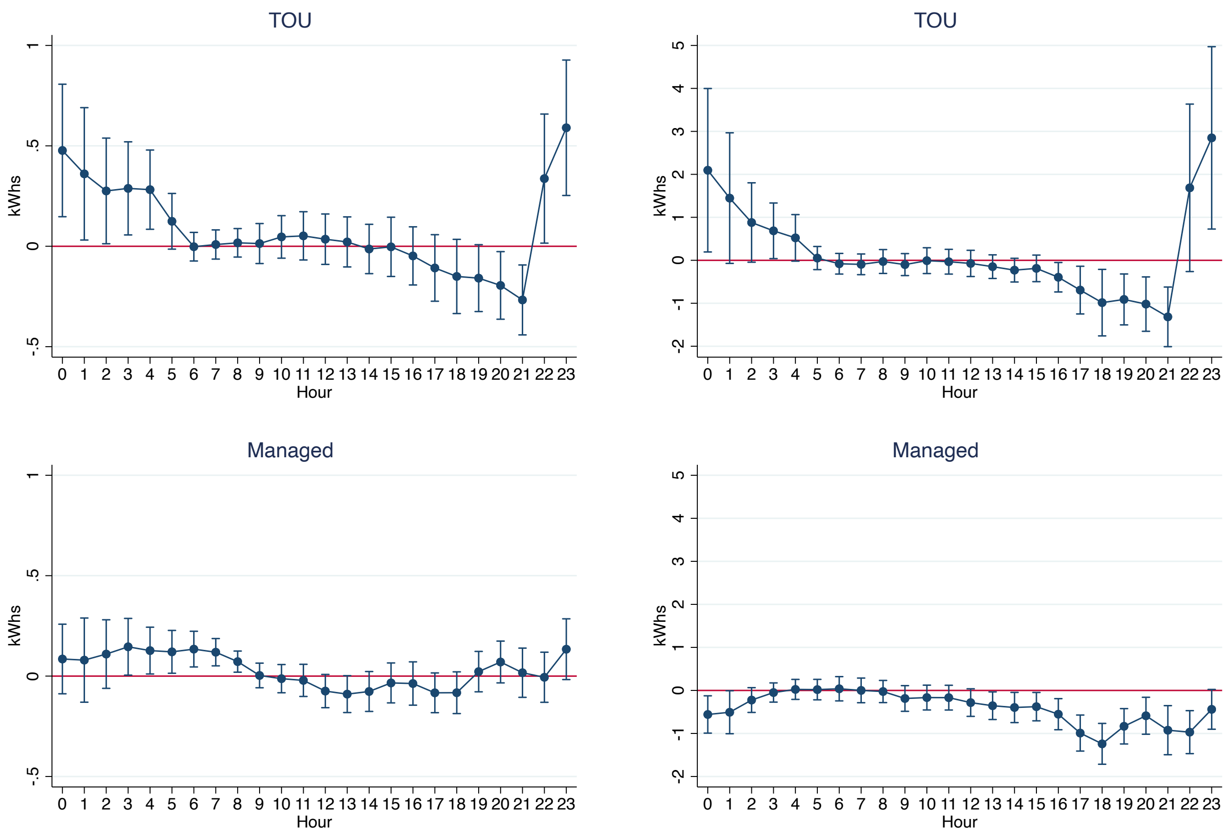
These findings demonstrate that while TOU pricing results in a systematic shift away from the peak hours, there is a large (coordinated) shift in charging to the off-peak hours. This causes a large increase in constraint violations in the off-peak, essentially creating a new and larger "shadow demand peak" of charging on a distribu-

[20]This calculation reflects $-0.5031/0.9838 \approx -0.51$ and $-0.5062/1.0237 \approx -0.49$ for the TOU and managed groups, respectively.

[21]The latter two calculations reflect $0.8297/0.6224 \approx 1.33$ for the TOU group and $-0.3062/0.6722 \approx -0.46$ for the managed group.

tion transformer. In contrast, managed charging results in a systematic reduction in distribution transformer constraint violations across both peak and non-peak hours.

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.

Figure 3a presents the estimated hourly treatment effects from the DID regression analysis using 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 the control group during the post-treatment period, compared to the pre-treatment period. For the TOU group, there is a reduction in evening peak hour charging and a systematic large and often statistically significant increase in off-peak hour charging. These results are consistent with EV owners in the TOU group delaying their charging from when they arrive home from work to late evening hours, aligning with financial incentives. In contrast, the managed group shows no systematic change in charge timing. There is a small statistically significant increase in morning charging kWh between 5 AM to 9 AM.[22]

Figure 3b presents hourly regression estimates using constraint violations as the dependent variable for both the TOU and managed groups. Consistent with the descriptive evidence above, the results indicate that the TOU treatment reduces the amount of distribution transformer constraint violations in the evening peak hours (before 10 PM) but lead to a large increase in the magnitude of constraint violations during off-peak evening hours with the coefficients for hours 23 and 0 being significantly different from zero. Several of the positive point estimates in the peak evening hours are larger in magnitude than the reductions in the evening off-peak hours.

In contrast, Figure 3b demonstrates that the distribution transformers with managed EVs experience a statistically significant reduction in violations during evening peak hours with no corresponding increase in violations during off-peak hours. In fact, negative and significant treatment effects persist during overnight off-peak hours. These results further demonstrate that the management of EV charge timing results in a systematic reduction in distribution transformer constraint violations relative to the control group.

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.[23]

5.2 Willingness to Provide Automated Flexibility

Our results indicate that managed charging can deliver peak time energy savings without creating shadow peaks that strain local distribution networks. 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 vehicle charging data with third parties and may require users to download and use third-party apps.

[22]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.

[23]See Valdberg et al. (2022) for drivers on TOU rates in California's Pacific Gas and Electric service territory and Appendix C.4 for drivers across 14 major U.S. cities using the Optiwatt App, who self-report being on a TOU rate.

Interestingly, we find little evidence of consumers being inconvenienced by or opposed to managed charging technology within our sample. We first consider the intensive margin, or the extent to which owners assigned to the managed group actively overrode being managed for a given charging session. Recall, an EV can override being managed by simply pushing a button in the app to start charging immediately. The override is registered with a time stamp. In the post-treatment period, there are 5,743 day-level observations when managed EVs are charged at home. There are only 44 managed overrides over this period, representing approximately 1% of all site-specific at-home charging days. EV owners rarely override managed charging. These findings are consistent with our regression results, which demonstrate a systematic reduction in constraint violations due to the permitted management of EV charging.

Second, we consider the extensive margin, or consumers' willingness to join or stay in a managed charging program. At the close of the experiment in December 2023, we added a question to the exit survey asking the 59 remaining consumers in the control group whether they would be willing to join the managed charging program and earn \$0.035/kWh credit for all charging at home. We randomized different one-time payment amounts to join the program, \$0, \$75, and \$150, each with equal probability. We found that of those who completed the survey, and were thus made an offer to join the managed charging program, respondents overwhelmingly accepted the offer. Of the 35 respondents that completed the survey, only one opted not to join managed charging, suggesting that the one-time payment levels did not deferentially affect take up.[24] Of the 34 that opted into managed charging, 28 remained after 6 months. The rates of consumers remaining in managed charging for six months from the group that had to actively opt-in to the program were similar to the rates observed from the experimental group which was automatically placed in managed charging and had to actively opt-out. While we are limited by the sample we recruited of current EV owners who agree to join a charging pilot, our findings are indicative of a substantial willingness to provide flexibility.

6 Discussion and Conclusion

As the 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

[24] The one EV that opted not to join was offered the \$0 upfront incentive.

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 this less of an issue. Whereas, at the more granular neighbourhood scale of the distribution network, load diversity cannot be safely assumed, thus raising the possibility of correlated charging behaviour (Cutter et al., 2021).

We find that TOU pricing is effective at shifting EV charging to off-peak hours as intended, but has the unintended consequence of exacerbating challenges for 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 constraint violations as compared to flat pricing. Our experiment demonstrates that this well-intentioned policy is likely to exacerbate the challenge of integrating a growing share of EVs and accelerate the need for costly infrastructure upgrades.

To quantify the impact on distribution transformer capacity requirements 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 across the groups reflect the extent of coincidental EV charging arising from treatment. The average maximum demand for a 10-EV distribution transformer 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. These results reinforce our findings that managed charging has the potential to reduce the need for distribution transformer upgrades compared to the status quo, while TOU can magnify them.

Dynamic pricing, under which the retail price changes hourly in line with real-time 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 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.

We find that an alternative solution, managed charging, can effectively resolve the coordination problem and appears well-tolerated in our study, with minimal overrides. 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.[25]

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. Managed charging for electric vehicles is currently far less common than TOU pricing but, as evidenced by this study, has the potential to directly resolve the coordination problem and reduce strain on distribution networks.

[25] In Alberta in 2023, the average difference between peak and off-peak wholesale prices was 7.5 cents/kWh, indicating that additional benefits could be potentially unlocked by accounting for generation costs in the managed charging algorithm.

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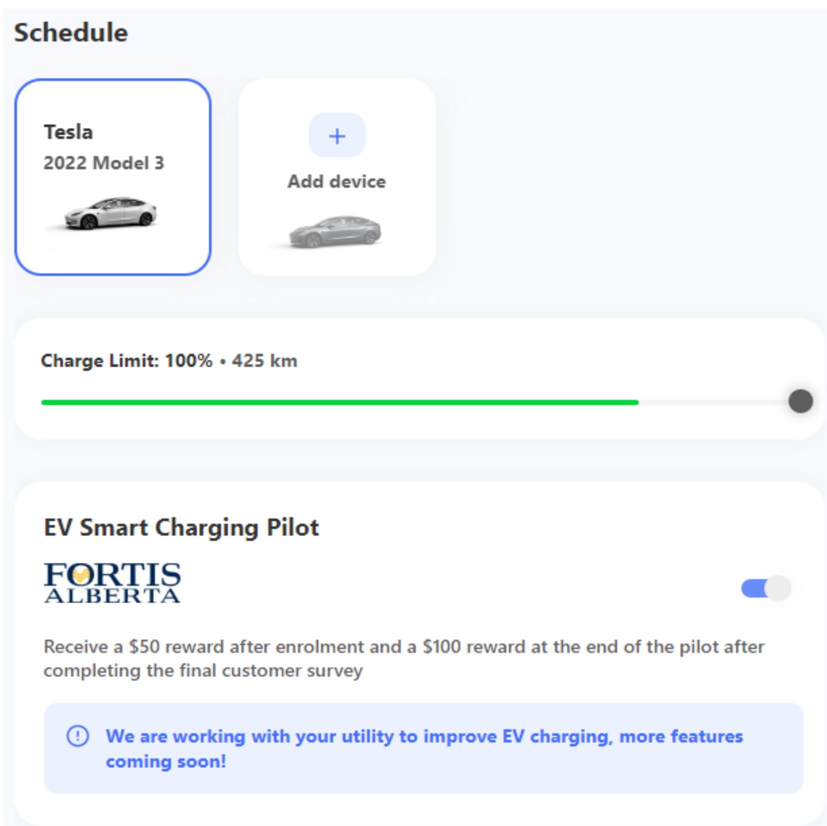
Appendices

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

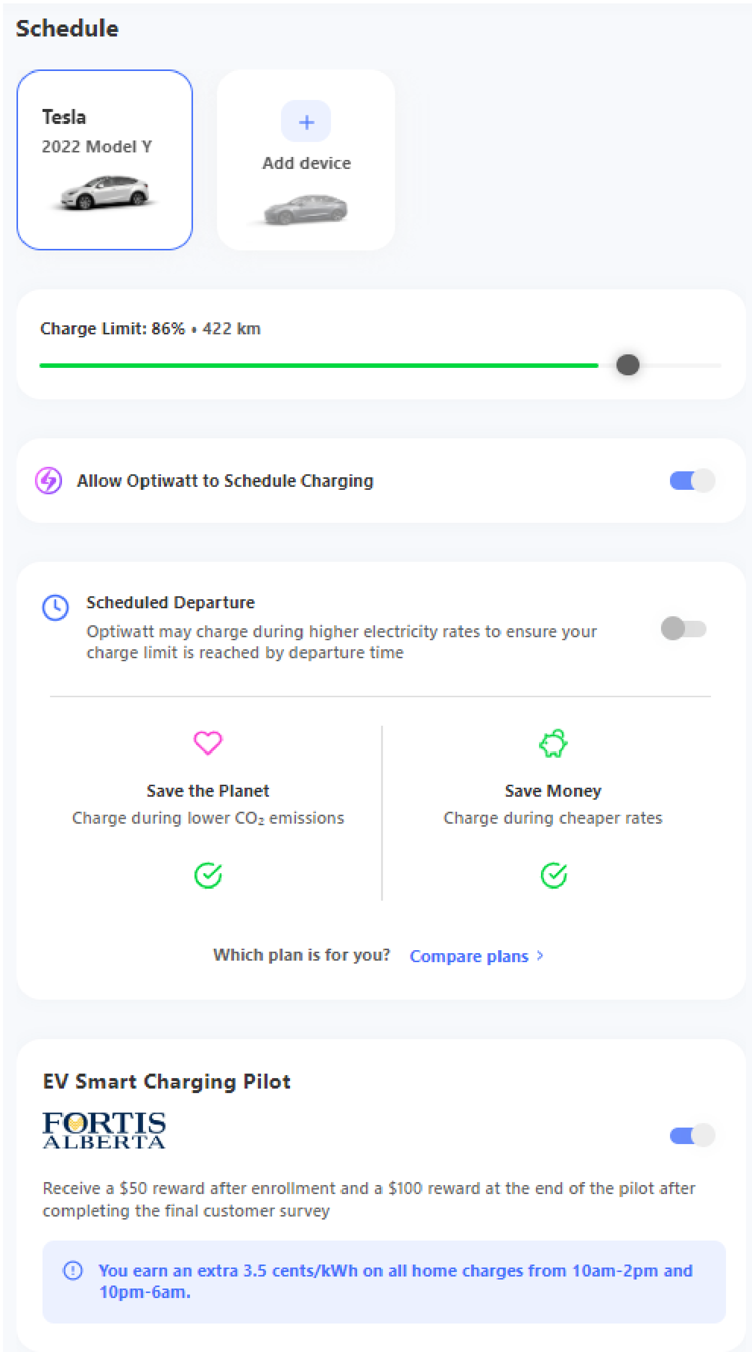
View the full FAQ

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

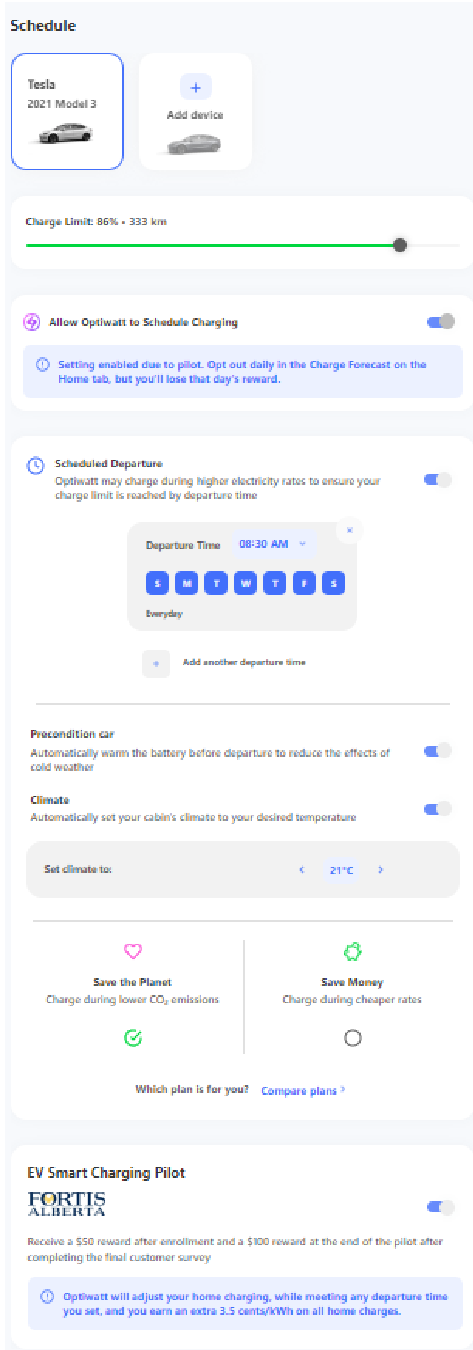
View the full FAQ

optiwatt

HOME | NEWS | FAQS

1540 Market St San Francisco, California 94102

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 CO_2 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 so-called "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 arises when they 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 assessed 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, which 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.

Second, Figure B.1 displays the number of cars that left the experiment over time. The attrition pattern is relatively smooth, with no immediate spike following the start of the experiment. This suggests that participants were not leaving due to dissatisfaction with their assigned treatment group but rather for other idiosyncratic reasons throughout the experiment. This pattern, taken together with the post-treatment comparison in Table B1, suggests that it is unlikely that those who left the experiment were responding differently to the treatment.

We now examine treatment effects over time. If drivers who left the experiment had systematically different driving behavior or were less or more responsive to treatment, we would expect to see effects either increasing or decreasing over time. Figure B.2 displays the cumulative kWh violations 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. Transformer-level hourly constraint violations is the outcome, and we include interactions between calendar month indicators and $\text{Post}_t \times \text{Group}_d$ as well as between calendar month indicators and $\text{Post}_t \times \text{Group}_d \times \text{Off Peak}_t$ as the main regressors. Figure B.2 plots the respective coefficients for these interaction terms. 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.3 we show the results of a similar analysis as in Figure B.2, focusing on the average transformer-level kWh charged per hour for vehicles that remain on the transformer. Here too, the average amount charged per vehicle at home is statistically indistinguishable over time. Figures B.2 and B.3 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.

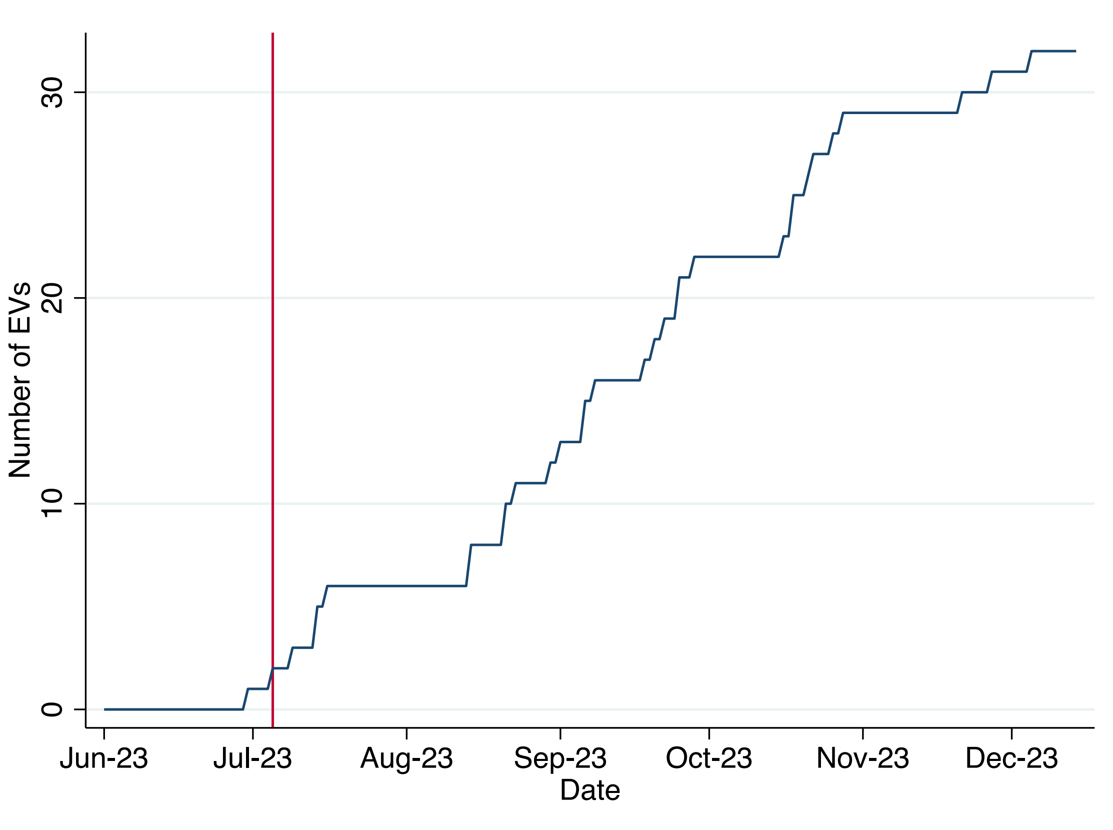
Finally, as we describe in Section 5.2, in December 2023 we offered the 59 remaining control customers to opt-in to a managed charging program that runs for 6 months. 35 respondents completed the survey and 34 opted into the program. 6 out of 34 (18%) EVs that opted into the managed program unenrolled. 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	

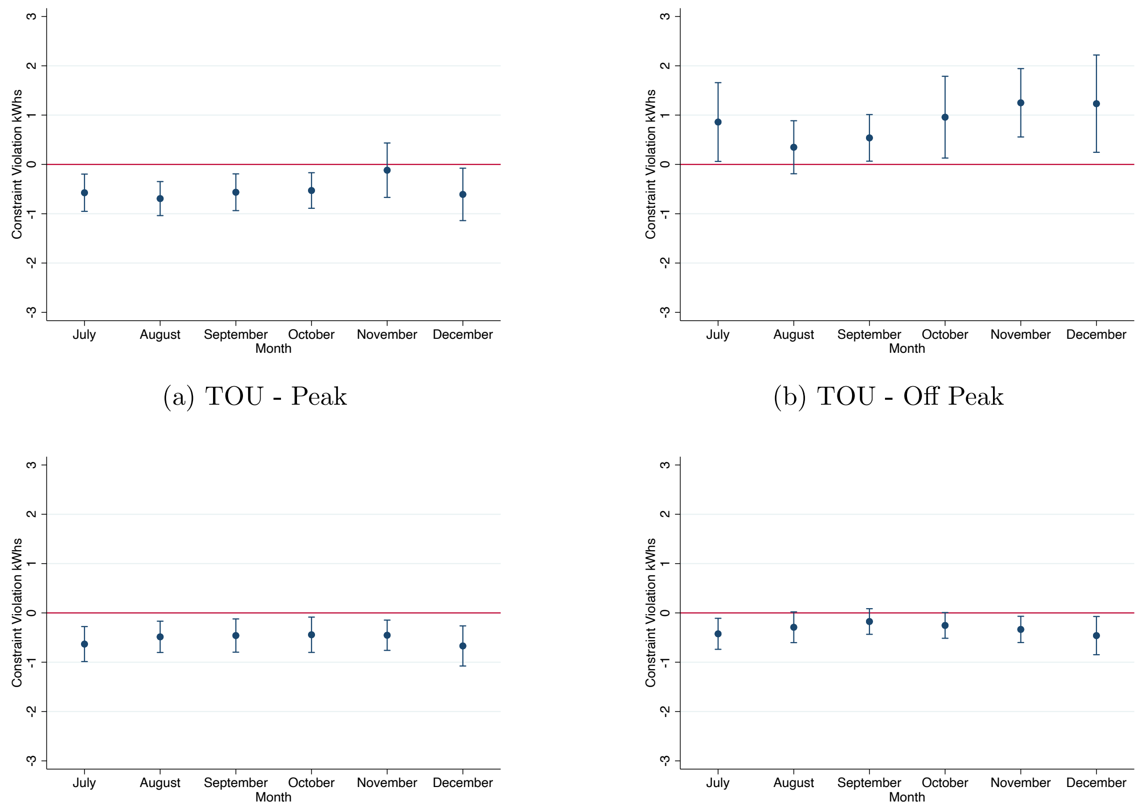
Notes. This table compares pre-treatment and post-treatment (during month of July) average values of various charging variables at the vehicle level separated by EVs that completed the experiment and those that left. Parentheses contain the standard deviations. Home Share represents the percentage of 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.

Figure B.1. Attrition over Time



Notes. The vertical line reflects July 5, 2023, the first day of treatment.

Figure B.2. Estimated Treatment Effects by Group and Month - Constraint Violations (kWh)



(a) TOU - Peak

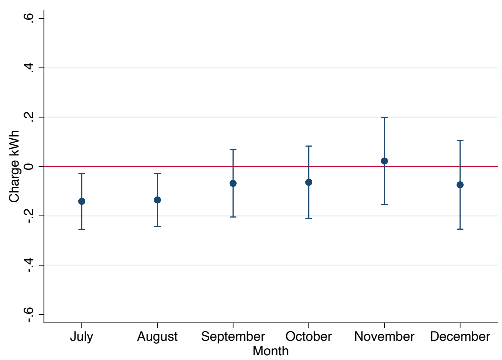
(b) TOU - Off Peak

(c) Managed - Peak

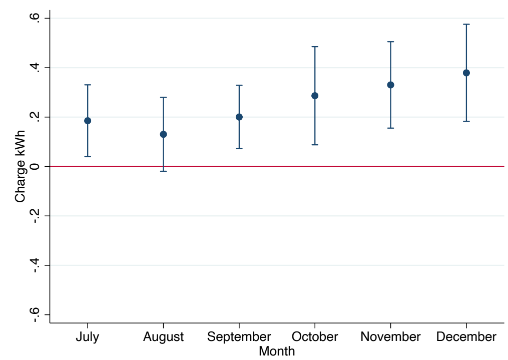
(d) Managed - Off Peak

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

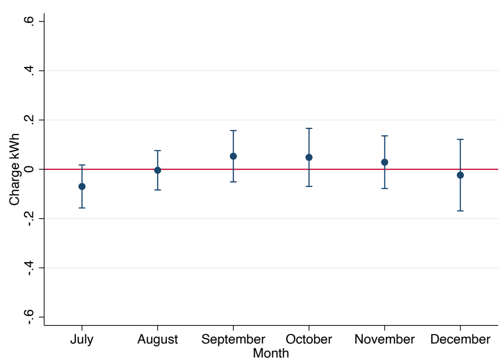
Figure B.3. Estimated Treatment Effects by Group and Month - Charged kWh



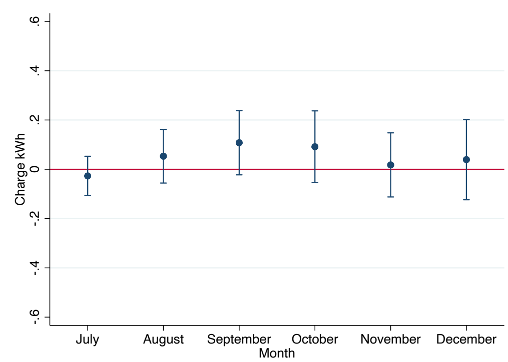
(a) TOU - Peak



(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 C2. Extensive Margin Analysis

	Charging Indicator		Charging kWh	
	Home-Only	Home and Away	Home-Only	Home and Away
TOU × Post	0.0133	0.0067	0.3783	1.0518
	(0.0266)	(0.0260)	(0.6454)	(0.8152)
Managed × Post	0.0169	0.0131	0.2183	-0.2060
	(0.0264)	(0.0258)	(0.6593)	(0.8428)

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 $^{***}p < 0.01$.

Table C2 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.

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 C3 evaluates how our Fortis sample compares to the non-TOU US EVs sample, using data covering our pre-treatment period. This assessment of balance corresponds to the same variables used 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.

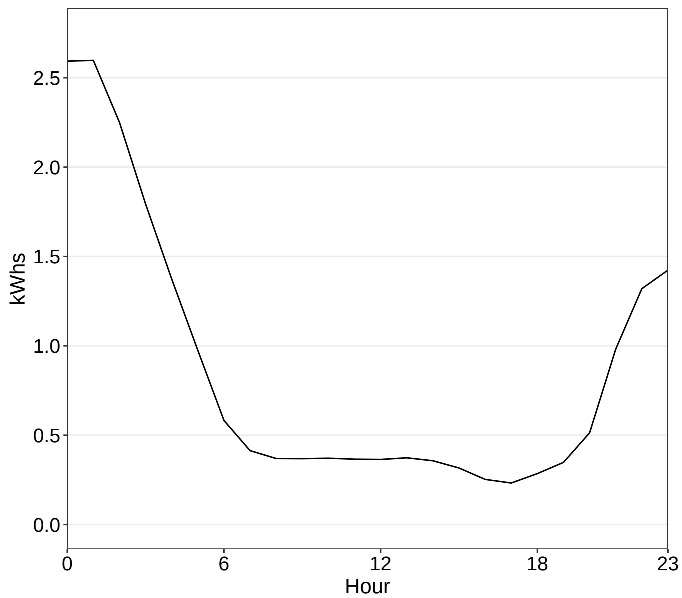
Second, we are interested in evaluating how the US EVs that report being on a TOU rate in the Optiwatt sample charge their cars at home. Figure C.4 shows the average hourly charging kWh at home on days where charging occurs using all 14 major US cities provided by Optiwatt. For consistency, we focus on our pre-treatment sample period. These descriptive results are consistent with our main findings. EVs on TOU rates in the US sample respond to the TOU price signal with 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).

Table C3. Balance on Observable Characteristics by Group 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.

Figure C.4. 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.