AER: Insights 2025, 7(4): 550–566
https://doi.org/10.1257/aeri.20240476

Electric Vehicles and the Energy Transition: Unintended Consequences of Time-of-Use Pricing†

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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. (*JEL* C93, D91, L62, L94, Q42)

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 that 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

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† Go to https://doi.org/10.1257/aeri.20240476 to visit the article page for additional materials and author disclosure statement(s).

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 (McKenna, Abraham, and Wang 2024). This local issue is enhanced by the fact that early EV adopters tend to be geographically concentrated (Elmallah, Brockway, and Callaway 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, Brown, Shaffer, and Wolak 2025; 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 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 ten 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 US-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 that they would receive 3.5 cents/kWh for charging at home during off-peak hours (10 AM–2 PM and 10 PM–6 AM).[4] Managed charging participants were told that they would receive 3.5 cents/kWh for all home charging

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

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

[4] All currency is in Canadian dollars unless otherwise noted. At time of writing, C\$1.00 $\approx$ US\$0.73.

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 corresponding 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 percent), 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, Brockway, and Callaway 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. McKenna, Abraham, and Wang (2024) forecast a 160–260 percent increase in US 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, Hernæs, and Imenes 2025). 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 signal local distribution constraints properly. 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.

I. 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, $\sum_{i=1}^{n} q_i$, 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 individual i'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:

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

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

(i) q_T increases with average peak demand, $\bar{q}_i$;

(ii) q_T increases as individual irregularities, σ_i, increase; and

(iii) 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 kW (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.

II. Experimental Design and Data

A. *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 the app 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 percent in rural regions (Statistics Canada 2024). Comparing participants' charging behavior to drivers in nine major US 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: control (62 EVs), TOU (70 EVs), and managed (70 EVs).[7] TOU and managed participants were defaulted into their treatment

[5] Fortis serves over 60 percent of Alberta's electricity distribution network, with over 600,000 end users. Residential households in its territory face retail rates that do not vary through the day but can change on a monthly basis.

[6] The US sample charges slightly longer daily (50 minutes more), but average daily energy charged (22.3 kWh versus 23.2 kWh) and peak power drawn (6.7 kW versus 6.8 kW) are nearly identical, indicating similar grid demands (Supplemental Appendix C2).

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

group and informed that 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 Supplemental Appendix A.

TOU participants were offered a 3.5-cent/kWh reward (paid via the Optiwatt app) for at-home charging during off-peak hours (10 AM–2 PM and 10 PM–6 AM), effectively reducing the volumetric price (i.e., per kWh) by about 19 percent. Managed participants were offered 3.5 cents/kWh for all at-home charging, with the condition that Optiwatt could adjust charging times to align with grid needs. The software ensured that 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 but forfeited the reward for that day.

B. *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 ten cars and analyze their aggregate behavior.[8]

Optiwatt passively monitored EV charging behavior in both the control and TOU groups without participants' awareness of their 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 that 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 of up to 200 percent of their nameplate capacity for short durations. However, sustained or frequent overloading significantly shortens the transformer's lifespan and increases the likelihood of failure (McKenna, Abraham, and Wang 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's territory, multiplied by ten to represent the ten 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

[8] There were seven virtual transformers in each of the control, TOU, and managed groups. We included one control transformer with only two 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.

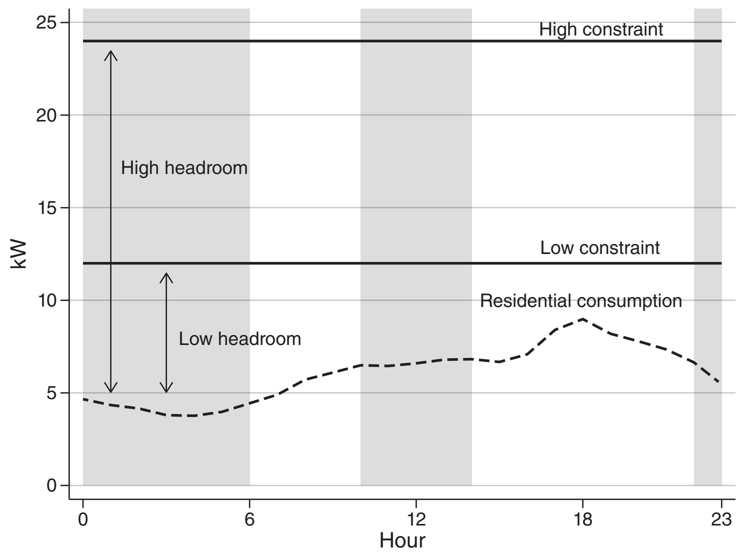

Figure 1. Illustration of Virtual Transformer Capacity

Note: Shaded areas represent off-peak hours.

on typical distribution transformer ratings (Hilshey et al. 2012; EnergyHub 2023). The 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.

C. *Data and Assessment of Balance*

Our data span from April 1 to December 13, 2023, covering each charging session's start and end times, kWh charged, charger power (kW), and location (home or away) (Bailey, Brown, Myers, et al. 2025). We also have information on vehicle characteristics, including make, model, year, and battery range.

We use pretreatment data to check balance across groups by comparing average EV charging metrics and vehicle characteristics. Table 1 shows that 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.

TABLE 1—BALANCE ON OBSERVABLE CHARACTERISTICS BY GROUP USING PRETREATMENT 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	7	7	7	

Notes: This table compares pretreatment 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 period either at home or away; and “off-peak share—home only” is the percentage of kWh charged in the off-peak period at home only. “Tesla” is the percentage of EVs that are Teslas, 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.

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 the TOU and managed groups are not statistically different, though both exceed that of the control group. In Supplemental Appendix B, we compare observables for vehicles that dropped out versus those that remained and find that 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

[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 posttreatment periods. However, the maximum charging rate (kW) is significantly higher posttreatment for attritors (8.60 kW) compared to nonattritors (6.99 kW).

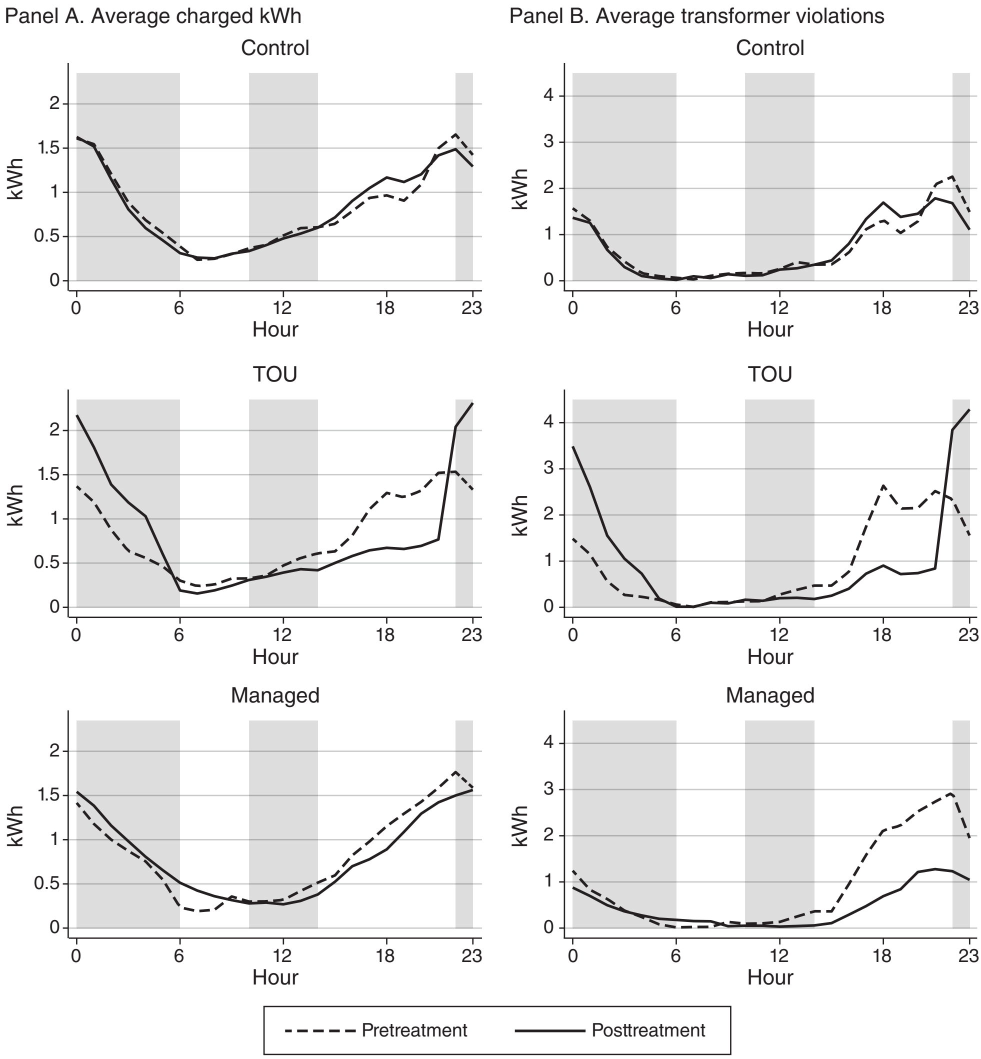

FIGURE 2. AVERAGE CHARGE KWH AND TRANSFORMER VIOLATIONS BY GROUP AND HOUR OF DAY

Notes: "Average charged kWh" reflects the mean hourly charging (kWh) across all vehicle days with nonzero 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 posttreatment periods. The shaded areas indicate off-peak hours.

the benefits of managed charging relative to the other programs. To account for this, we perform a bounding exercise, described in Section IVB, where attrited vehicles are assigned control group behavior to calculate treatment effects.

III. 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 left-hand side of Figure 2 shows mean hourly charging (kWh) across vehicle days with nonzero home charging by group.[11] The shaded areas indicate off-peak hours. Pretreatment charging profiles are similar across groups, with higher mean charging starting at 6 PM and continuing overnight.

The control group shows no change in charging behavior between pre- and posttreatment, 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 (5 PM–10 PM), 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 peak to off-peak.

The right-hand side of Figure 2 summarizes the average hourly distribution transformer constraint violations (in kWh) by group pre- and posttreatment. Pretreatment, 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 posttreatment, we see consistent patterns of constraint violations for the control group. In contrast, the TOU group displays a sharp increase in constraint violations posttreatment 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 pretreatment, demonstrating that TOU has the potential to accelerate the need for transformer upgrades. In contrast, the managed group shows a consistent reduction in violations posttreatment. Unlike the TOU group, they reduced peak violations without any corresponding increase in off-peak hours.

IV. Empirical Strategy and Results

A. *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 quantify these effects more formally. 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:

$$
\begin{aligned}
(3) \qquad Y_{idh} = {} & \beta_0 + \beta_1 Post_d \times TOU_i + \beta_2 Post_d \times Managed_i \\
& + \beta_3 TOU_i \times OffPeak_h + \beta_4 Managed_i \times OffPeak_h \\
& + \beta_5 Post_d \times OffPeak_h + \beta_6 Post_d \times TOU_i \times OffPeak_h \\
& + \beta_7 Post_d \times Managed_i \times OffPeak_h + \alpha_i + \delta_d + \tau_h + \epsilon_{idh},
\end{aligned}
$$

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

[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. Supplemental Appendix C1 provides evidence that drivers did not shift charging locations posttreatment.

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 one starting on July 5, 2023 (posttreatment), and zero otherwise. $Managed_i$ and TOU_i are indicator variables that denote whether EV i is in the managed or TOU groups, respectively. $OffPeak_h$ equals one if hour h falls within our definition of off-peak hours and zero 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 group 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 percent relative to the control group's posttreatment mean ($-0.203/0.369 \approx -0.55$), while off-peak charging increases by 54 percent ($0.229/0.422 \approx 0.54$). 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 section of Table 2 presents the results of Wald tests assessing the null hypothesis that the estimated treatment effects for the TOU and managed groups 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 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,

[13] For this analysis, we include all vehicle days, not just those with nonzero at-home charging as in Figure 2.

[14] Supplemental Appendix C3 provides results clustering at the vehicle level for all treatment groups, with somewhat tighter standard errors.

[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 zero otherwise.

Table 2—Estimated Treatment Effects by Group

Group	Hours	*Charge kWh* (1)	*Constraint Violations* (2)
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 dependent variable (posttreatment)			
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 the TOU and managed groups by peak and off-peak hours, with *p*-values reported in brackets for the Wald tests assessing the null hypothesis that the estimated treatment effects for TOU and managed are equal. "Mean dependent variable (posttreatment)" represents the mean value of each dependent variable between April 1, 2023, and 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 column 2 includes transformer-level fixed effects. Standard errors (in parentheses) in column 1 are clustered at the transformer level for vehicles assigned to the managed group and the EV level for vehicles assigned to the control and TOU groups. Standard errors in column 2 are clustered at the transformer level.

reflecting the shift in the unit of observation from EV hour to transformer hour. Standard errors are clustered at the transformer level.[16]

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 percent $(-0.772/0.906)$ and 79 percent $(-0.720/0.906)$ of the control group's mean posttreatment peak constraint violations, respectively. However, the TOU group exhibits a significant 139 percent $(0.961/0.689)$ 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.

[16] Supplemental Appendix C3 demonstrates that our results are robust to implementing wild bootstrap robust standard errors to address potential concerns of having only 21 transformer clusters.

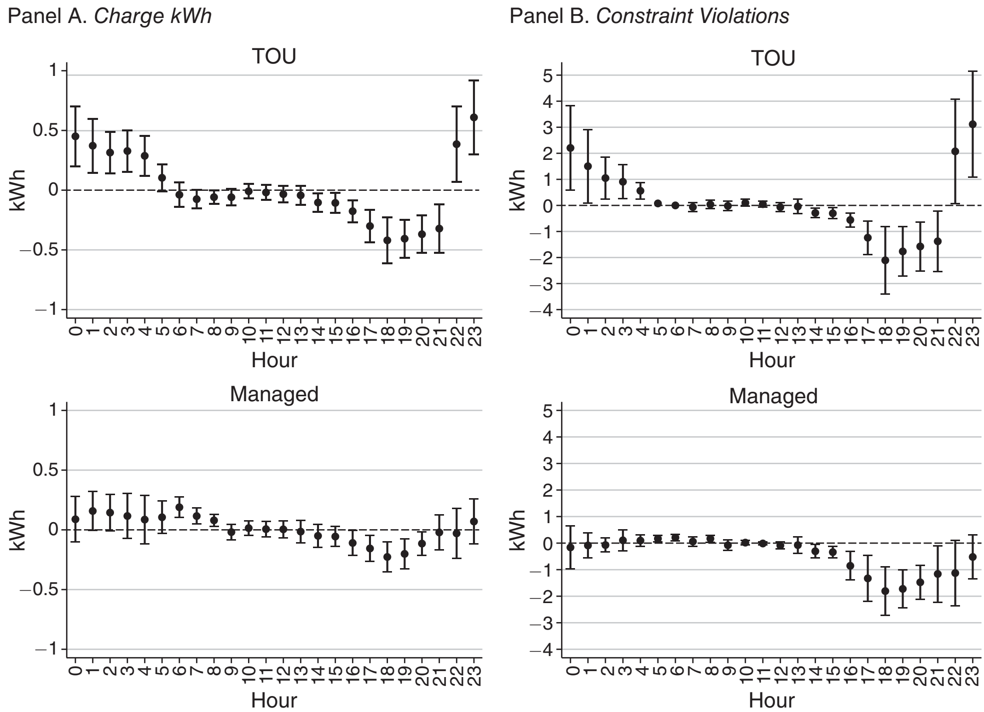

FIGURE 3. ESTIMATED TREATMENT EFFECTS BY GROUP AND HOUR

Note: The upper and lower bars represent the 95 percent confidence interval.

To estimate the hourly effect of TOU and managed charging, 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 the control group during the posttreatment period compared to the pretreatment 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 and 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

[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.

are larger in magnitude than the reductions in the evening peak hours. In contrast, the transformers with managed EVs experience a significant reduction in violations during evening peak hours with no corresponding increase during off-peak hours.[18]

B. *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 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 posttreatment period, across 5,743 instances of managed charging at home, only 44 (less than 1 percent) 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 II, attrition rates were higher in the managed group compared to the TOU and control groups. 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 Supplemental Appendix Table B2. However, from this analysis, the difference between the estimated treatment effect for off-peak constraint violations for the TOU group minus that of the managed group (1.047) is close to those reported in Table 2 in the main text (1.108), suggesting that differential attrition from the managed group does 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 onetime 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 (29 out of 34 remained after six 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.

[18] Supplemental Appendix C4 shows that these results become more pronounced as transformer constraints become tighter.

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

V. 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., statewide 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 that TOU pricing is effective at shifting EV charging to off-peak hours but 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 posttreatment 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 ten-EV distribution transformer (i.e., q_T from equation (2)) under TOU pricing is 24 percent higher than the control group posttreatment. In contrast, the average maximum demand for the managed group is 17 percent lower than the control and 33 percent lower than TOU posttreatment.[20] 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.

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, for example, due to living in commuter neighborhoods. As such, one could reasonably expect more correlated behavior in a physical transformer setting. We explore this by regrouping the passively monitored TOU and control participants into virtual transformers based on a clustering analysis of similar characteristics. The results of

[20] A simulation exercise shows that 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 (Supplemental Appendix C6).

this exercise (detailed in Supplemental Appendix C5) 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 nonexperimental load shapes for drivers on TOU rates across the United States, 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-cent 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 cents and 22 cents, respectively, and California's Pacific Gas & Electric Company has EV-specific TOU rates with differences as wide as US$0.36 (C$0.50) (BC Hydro 2024; Government of Ontario 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.

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[21] See Valdberg et al. (2022) for drivers on TOU rates in California's Pacific Gas & Electric service territory and Supplemental Appendix C2 for drivers in 14 major US cities using the Optiwatt app who self-report being on a TOU rate.

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