The Social Value of Managed Electric Vehicle Charging

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January 6, 2025

Abstract

As growing renewable energy makes electricity supply more variable and data centers and electric vehicles (EVs) increase demand, optimally managed EV charging is increasingly socially valuable. This paper develops and implements a methodology for non-experimentally estimating the effects of managed charging on electricity load and the economic value of those effects. We exploit proprietary data from the largest managed charging optimization provider, covering 27,000 vehicles at 17 utilities nationwide with 15-minute data. Event study estimates show that on average, managed EV charging reduces daytime charging electricity load by about 25 percent while increasing nighttime load by about the same proportion. On average across programs, managed charging reduces drivers' charging costs by 2.6 percent, reduces utilities' electricity supply cost by about 2.9 percent, and increases total surplus by $15 per year per vehicle.

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1 Introduction

The global push toward decarbonization is dramatically reshaping both supply and demand for electricity. On the supply side, fossil fuel generation is being replaced by wind and solar power, which generate only when the wind is blowing and the sun is shining. On the demand side, natural gas heating and gasoline vehicles are being replaced by electric heating and electric vehicles. Between these two trends is a critically important challenge and opportunity: making electricity demand more flexible, so that it can respond to variation in supply and avoid overloading the distribution grid.

Many analysts believe that "managed charging" of electric vehicles (EVs) may be the single biggest opportunity for demand-side flexibility. EVs require significant amounts of electricity: fully charging an electric vehicle overnight requires a "level 2" charger that draws five to ten times the average power flow to an American home. Currently, most drivers plug in their EVs when they arrive at home in the early evening, after which the car charges for several hours and then sits idle until a morning trip. This imposes two costs. First, wholesale electricity generation has relatively high private and social costs in the early evening, as the sun goes down and fossil fuel power plants ramp up to make up for the loss of solar power. Second, neighborhood-level electricity distribution infrastructure must be upgraded more quickly if demand increases further at peak times instead of becoming more smooth over time. To reduce these costs, electric utilities are beginning to implement managed EV charging programs, which automatically charge vehicles in a coordinated least-cost manner.

As we detail below, there are many existing forward-looking evaluations of managed charging that consider the potential of hypothetical programs. However, the human and technological nuances of actual managed charging initiatives could differ substantially from an idealized model: for example, drivers self-select into programs, drivers can override program settings, and charging optimization algorithms optimize for multiple objectives and have subtle practical constraints. There are now also a few small-scale evaluations of managed EV charging, perhaps considering a few hundred vehicles and optimizing for one particular objective (e.g., Bailey et al. 2024b). But the actual economic impacts of managed charging, in the wild and at scale, remains an empirical question.

We measure the social value of managed EV charging using data from WeaveGrid, the largest managed charging service provider in the US. Over the course of our data beginning in June 2023, WeaveGrid has worked with 27,000 vehicles from 17 utilities. The utilities that WeaveGrid works with serve more than 40 percent of EVs in the United States.

Our paper begins by providing descriptive evidence on unmanaged EV charging. While straightforward, this evidence is important because forecasts of future electricity load and the value of managed charging hinge on the profile of when electric vehicles currently charge, with very different estimates currently in the literature. Across all hours, the average charging load is somewhat under 1 kilowatt (kW), representing about half of the average American home. But 64 percent of charging load occurs between 9PM and 6AM, and load rises to almost 3 kW in the midnight to 1AM hour. About 70 percent of charging events are at home (mostly in the evenings), while charging away from home peaks between 9AM and 5PM. Compared to vehicles on flat (time-invariant) electricity pricing schedules, vehicles on time-of-use (TOU) schedules consume less from 3PM to 9PM, and more from midnight to 6AM. Most vehicles follow one of two charging patterns: "charge now," ie., they charge immediately when plugging in, or "charge at X," i.e., they are programmed to begin charging at a specific time each day, which varies across vehicles.

We then present a new methodology for non-experimental estimates of the causal effects of managed charging on electricity load shifting. This non-experimental methodology is particularly valuable given that in practice, most managed EV charging programs are not implemented as randomized experiments. We use an event study design, comparing a vehicle's charging patterns after versus before beginning managed charging to a control group of unmanaged vehicles over that same period. We observe sharp changes in load shapes immediately when vehicles begin managed charging, suggesting that non-experimental event study evaluations credibly deliver average causal effects.

We find that managed charging significantly shifts average load across the hours of the day. After adopting managed charging, average charging load decreases between 5AM and 9PM, by an average of about 0.15 kW/vehicle, or about 25 percent of average unmanaged charging load during those hours. Offsetting this, charging load increases sharply between 9PM and 5AM, by an average of about 0.35 kW/vehicle, or about 25 percent of average unmanaged charging load during that period.

The effects of managed charging adoption also exhibit heterogeneity along different dimensions. First, we find that for those vehicles on flat rate (time-invariant) electricity pricing schedules, managed EV charging tends to shift loads more towards the period between 9PM and midnight. This is because shifting charging timing will not change the cost to drivers on flat rate schedules, but the cost of electricity supply and the grid congestion will both be lower. For those vehicles on time-of-use (TOU) rate schedules, adopting managed charging results in a more dispersed load shift between 11PM and 4AM. Since TOU rate schedules have already shifted average loads towards the period after 21:00, which is a common peak rate end time, dispersing the load shift will be more effective in reducing congestion. Moreover, we examine the heterogeneous effects under different types of optimization objectives, which the electric utility dictates to WeaveGrid's optimizers. We focus on the two most common optimization objectives: utility price signals, which aims to reducing utilities' total cost of electricity supply, and grid forecast signals, which are designed to mitigate the grid congestion. When the system prioritizes minimizing costs of electricity supply with utility price signals, the load is primarily shifted from the late afternoon and early evening to the period after 9PM. On the other hand, when the system prioritizes smoothing load with grid forecast signals, the load is shifted further into the night, from the late afternoon and evening to after midnight and early morning hours. These results underscore the distinct load shapes under varying optimization goals of the system.

Having estimated the hourly effects on electricity consumption, we quantity the total surplus gains and distributional effects of managed charging, incorporating cost savings to drivers and utilities, environmental externalities, and wholesale price responses. We find a strong negative correlation such that managed charging shifts load away from hours with high retail/wholesale electricity prices to low retail/wholesale electricity prices. However, there is no significant relationship between load shifts and marginal environmental externalities from electricity generation. Overall, managed EV charging reduces retail electricity costs for drivers by about \$60 per vehicle-year, or 2.6 percent, and reduces utilities' wholesale electricity acquisition costs by about \$12 per vehicle-year, or 2.9 percent. The effect on monetized power plant pollution emissions is relatively small—only a decrease of 1 dollar per year per vehicle. On net, managed charging increases total surplus by around \$15 per vehicle-year.

These numbers imply important redistributive effects. In the short run with fixed retail prices, managed charging programs shift $\$60-\$12=\$48$ per vehicle-year of retail profits from the utility to charging program participants. Since participants are typically paid—for example, a \$75 enrollment bonus for Pacific Gas and Electric customers—this further shifts surplus from the utilities to consumers. In the longer run, regulators allow retail prices to increase in order to hold constant utility profits at their regulated rate of return. Thus, managed charging will result in a meaningful transfer from the general ratepayer population to EV owners, who are relatively wealthy.

Because of the time-sensitive nature of this topic and the ongoing data flow, today's draft is limited in several ways relative to what we expect to have in the near future. First, we will expand our analysis of the value of deferring distribution grid upgrades, using data from an ongoing PG&E pilot program. Second, we will estimate the short-run equilibrium effects on wholesale electricity prices. Depending on the supply elasticities at the times the managed charging increases versus decreases system demand, this will generate benefits and costs to all electricity consumers in the market.

Our research contributes to the following strands of the literature. First, this paper adds to the literature on the evaluation of managed charging programs. Bailey et al. (2024b) is the most related work, in which the authors implement a field experiment to evaluate how time-of-use schedules and managed charging shape drivers' charging behavior. Compared to Bailey et al. (2024a), our paper focuses on managed charging with large-scale non-experimental programs. Moreover, due to an overlapping of managed charging and time-of-use schedule, our paper further explores the combined consequences of both programs, while the Bailey et al. (2024a) allows them to compare TOU to managed charging, but not evaluate the combined effects of both. There is also other work examining the benefits of managed charging (Zhang et al., 2018; Blonsky et al., 2021; Anwar et al., 2022; Mills et al., 2023). Overall, a complete benefit-cost evaluation with real-life charging data and managed charging program is still lacking. Our work fills in this gap and incorporated the benefits and costs to utilities and EV owners.

More broadly, there is a surge in the recent research about the EV charging (Heid et al., 2024; Bailey et al., 2024b; Garg et al., 2024). Our paper focuses on managed charging which could be valuable to address the load surge from fast-growing EV industry. Moving forward, one important question to answer is how shall the utilities and grid system be prepared for the prospective rapid growth of EV in the U.S. (Elmallah et al., 2022; Jenn and Highleyman, 2022), and managed charging provides a potential solution. Therefore, understanding its consequences is essential for the future grid. Moreover, this research explores the social benefits of electrification, complementing other recent work such as on heat pumps (Bernard et al., 2024; Davis, 2024). This research also implements a novel quantitative exercise to measure the cost and benefit of a new technology (Cahana et al., 2022; List et al., 2018).

The rest of this paper is organized as follows. Section 2 describes the industry background as well as managed charging. Section 3 introduces the data and provides a set of descriptive evidence. Section 4 presents the empirical strategy, and Second 5 discusses results on load shapes and summarizes the heterogeneity analysis. Section 6 quantifies social values of managed charging. Section 7 concludes.

2 Background

2.1 Managed EV Charging

EV sales in the U.S. rose from fewer than 100,000 in 2013 to approximately 1.2 million in 2023, representing 7.6 percent of new vehicle sales that year.[1] Moreover, the U.S. Energy Information Administration projects that EVs will account for about 20 percent of new light-duty vehicle sales by 2050.[2] The prospective rapid adoption of electric vehicles is a crucial step for the electrification of transportation and one of the important pathways in the broader green transition.

Electric vehicles provide environmental benefits as they reduce greenhouse gas emission by

[1] The source of statistics is https://www.coxautoinc.com/market-insights/q4-2023-ev-sales/#:~:text=Data%20Point-,A%20Record%201.2%20Million%20EVs%20Were%20Sold%20in%20the%20U.S.,Estimates%20from%20Kelley%20Blue%20Book.

[2] The source of statistics is https://www.eia.gov/todayinenergy/detail.php?id=56480.

the replacement of gasoline-power vehicles. However, the rapid growth of EVs is driving a steep increase in charging demand, raising concerns about when drivers choose to charge their vehicles. If vehicles are plugged in during evening peak, when people typically return home from work, the load surge might stress local power distribution infrastructure. This could potentially lead to grid instability, higher operation expenses, and costly facility upgrades. Moreover, evening peak hours often correspond to the highest wholesale electricity prices, as well as retail rates for vehicles on time-of-use (TOU) schedules, resulting in increased costs for both utilities and drivers.

One solution to these concerns is to implement managed EV charging. According to the Department of Energy, managed EV charging is defined as "the strategic management of when and how the electric vehicles are charged without compromising the operational needs."[3] Managed charging offers three key benefits. First, it saves the charging expenditures for the owners by avoiding peak retail rates. Second, it could lower the electricity procurement cost for utilities by avoiding peak wholesale electricity price, contributing to a more efficient grid operation. Third, it protects the distribution assets and delays the costly update of the local distribution infrastructure. Managed charging could be a pivotal technology to balance rapid EV growth with the need for a stable and cost-efficient electricity grid.

2.2 WeaveGrid and Utility Programs

We collaborate with WeaveGrid to examine the impacts of managed EV charging. WeaveGrid is a leading managed charging program provider, founded in 2018. It collaborates with 17 utilities nationwide such as Pacific Gas & Electric Company (PG&E), Baltimore Gas and Electric (BGE), Xcel Energy, et at..[4] WeaveGrid has implemented 31 programs since June 2020: 13 of them are managed charging programs, while 18 of them are monitoring programs to monitor vehicles in unmanaged comparison groups.

A typical utility program is implemented in a few steps. First, the utility offers cash rebates to incentivize EV owners to sign up for managed charging programs. Upon signing up, WeaveGrid verify eligibility of candidates based on EV makers and home zip codes. Once the registration is complete, drivers could set preferred charging patterns, such as when EVs need to be ready for departure on weekdays and weekends, and the target battery state-of-charge. Moreover, drivers can choose whether to enact the low battery protection such that the charging will immediately start upon plugged in if the battery state-of-charge is below 20 percent. An example of the drivers setup interface is shown in Panel (a) of Figure 1.

Every time a vehicle is plugged in for charging, WeaveGrid will optimize charging timing based on the current state-of-charge, the target state-of-charge, the ready-by-time, as well as a mixtures

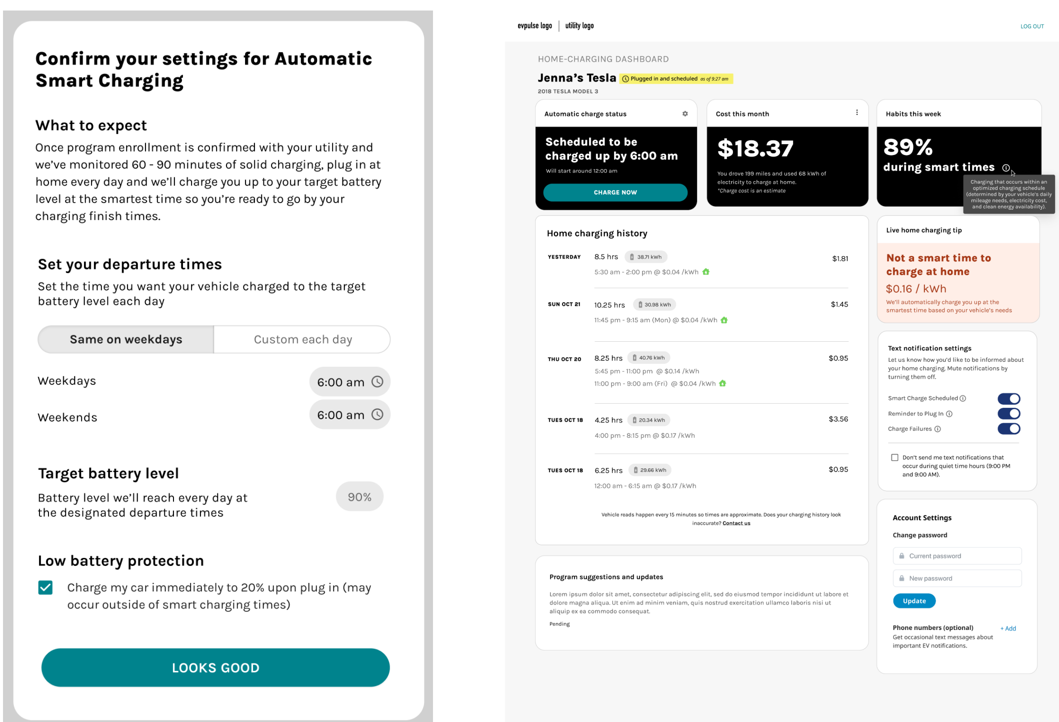
[3]The definition is sourced at https://www.energy.gov/femp/managed-ev-charging-federal-fleets.

[4]A list of of collaborating utilities is posted on https://www.weavegrid.com/utilities.

of signals sent by utilities. There are three major types of signals: retail rate schedules (i.e., rate plan signal), costs of electricity supply (i.e., utility price signal), and how congested is the local grid (i.e., grid forecast signal). The actually signals received by the program can be a combination of three signal types, but the rate plan signal is always incorporated, and thus minimizing consumer charging cost is prioritized by the program. Importantly, drivers don't fully yield the control of their vehicles, as they have the flexibility of overriding the optimization results, in case of for example, urgent use of the vehicle amid charging sessions. Overall, WeaveGrid program optimizes for the cost saving for drivers, the cost efficiency of utility electricity supply, and the stability of the local distribution grid, without compromising the convenient usage of the EV. Drivers could check the current automatic charge status, the total charging cost, and the home charge history on the program dashboard, as shown in Panel (b) of Figure 1.

Figure 1: User Interface of Managed Charging

(a) User Interface **(b)** Dashboard



Notes: This figure shows examples of the user interface and dashboard of managed charging. The screenshots are prepared by WeaveGrid.

3 Data and Descriptive Evidence

3.1 Data

Our main data set is proprietary and compiled from WeaveGrid, encompassing approximately 4 million charging events from 27,000 vehicles between June 1, 2023 and September 30, 2024. This data offers extensive geographical coverage, including 17 utilities and about 2,100 zip codes. Moreover, this data provides rich and granular charging information, including the timestamps and state-of-charge at the start and end of each charging event, as well as the amount of energy delivered at a 15-minute interval. For every charging event, we access following supplemental information, such as when the driver parks and departs, when the driver plugs in and unplug the charger, whether the charging is managed, whether the charging is optimized if managed, whether it occurs at home, and the signals received from the utilities for optimization. For each vehicle, we also obtain its rate schedule, which enables us to investigate interactions between time-of-use (TOU) pricing and managed EV charging.

Our main source of identification variation for the impacts of the managed charging is the vehicle-level timing differences in the managed charging adoption. We define managed charging adoption time as the first time when a charging event is managed for the focal vehicle during the sample period. To avoid the spurious definition of managed charging adoption, we keep the vehicles that are observed at least for 10 days in the sample, including at least 5 days before their first managed charging events. Moreover, we focus on 13 utilities with balanced numbers of vehicles that have adopted the managed charging program and those that have not. The detailed description of the data cleaning procedures are discussed in Appendix Section A.

The rest of this section first describes the charging patterns of vehicles that haven't adopted the managed charging program, and then examines how the charging patterns change before and after the managed charging adoption.

3.2 Charging Patterns without Managed Charging

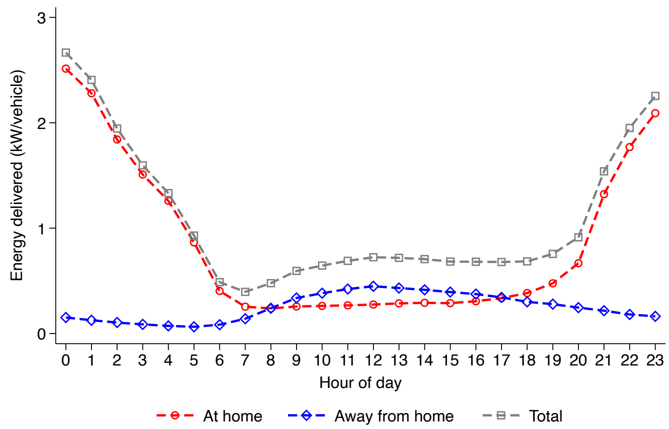
We describe the basic charging patterns in Figure 2, focusing on charging events that are not under the managed charging. A vehicle on a charging day consumes 24 kWh on an average charging day, 64 percent of which is delivered between 21:00 and 6:00 (on the next day), and 36 percent of which is delivered between 6:00 and 21:00. Among all the charging events, 73 percent occur at home, which constitutes 69 percent of the total energy delivered. Charging events at home and away from home also exhibit distinct patterns within a day: energy consumption for charging events at home peak between 21:00 and 6:00 (on the next day), while energy consumption for charging events away from home peak between 9:00 and 17:00. The load shape appears to have limited variation across seasons, while the charging load is higher during weekends compared to weekdays as shown in Appendix Figure A5.

Moreover, 52 percent of the charging events are under the time-of-use (TOU) pricing. Although the load shapes for charging events under the time-of-use (TOU) pricing and flat rate schedule are similar, we find that the TOU pricing tends to shift the load away between 15:00 and 21:00 to after the midnight. Consequently, the total energy delivered between 15:00 and 21:00 is lower by 25 percent under the TOU pricing compared with that under the flat rate schedule.

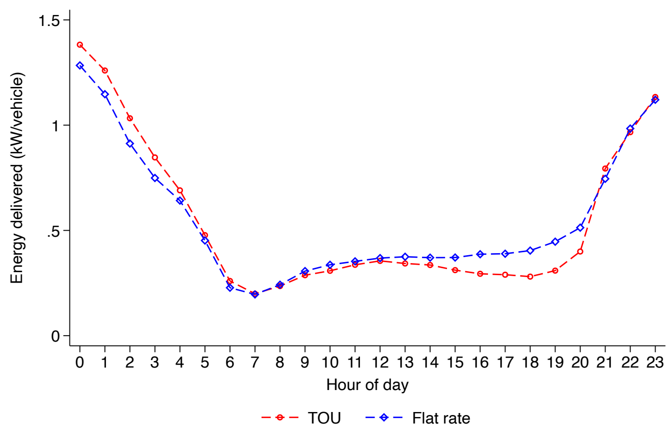
Drivers have distinct charging patterns. We categorize drivers into three charging types. First, drivers might charge as soon as they park the vehicle and plug in the charger (i.e., the charge-now pattern). Second, drivers might charge at a certain time according to the personal habit or the default set up of the charger (i.e., the charge-at-X pattern). Third, drivers that are under the TOU pricing might charge as soon as the peak rate time ends (i.e., the TOU pattern). We plot the distribution of the likelihood for these three types of charging patterns in Appendix Figure A6. Among vehicles that haven't adopted the managed charging, around 41.7 percent of them follow the charge-now pattern and around 13.0 percent of them follow the charge-at-X pattern. However, the proportion of vehicles that follow the TOU pattern is negligible. The rest half of the vehicles seem to have relatively random charging behavior that can be explained by neither when they plug in the charger nor the vehicle fixed effects.

Figure 2: Load Shape for Never-Managed Vehicles

(a) At Home v.s. Away from Home



(b) TOU v.s. Flat Rate

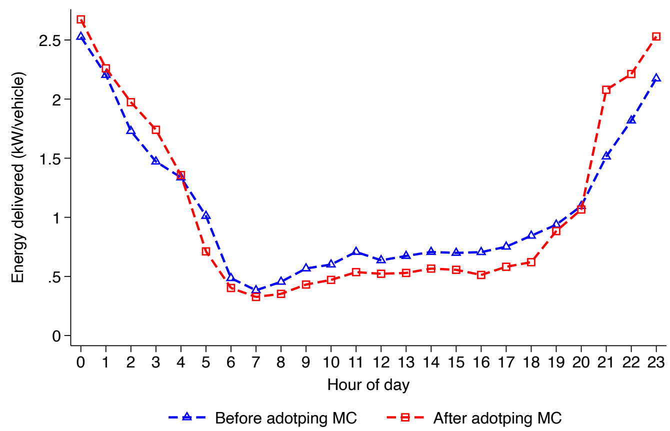


Notes: This figure illustrates the average load across the hours of a day for vehicles that are never managed during the sample period. Panel (a) presents the average load, further decomposed into home charging and away-from-home charging. Panel (b) provides a breakdown of the average load based on charging events under time-of-use rate schedules and flat rate schedules.

3.3 Load Shapes Before and After Managed Charging Adoption

We compare the load shapes of vehicles before and after they adopt the managed charging programs, as shown in Figure 3. We find that the managed charging programs shift the load during the day time to after 21:00. The average hourly load is reduced by 0.16 kWh per vehicle per day between 9:00 and 19:00, while the average hourly load is increased by 0.26 kWh per vehicle per day between 21:00 and 5:00 (on the next day). As 21:00 is typically the end of the evening load peak hour, the raw data pattern suggests the effectiveness of the managed charging program in shifting the load shape.

Figure 3: Hourly Load before and after Managed Charging Adoption



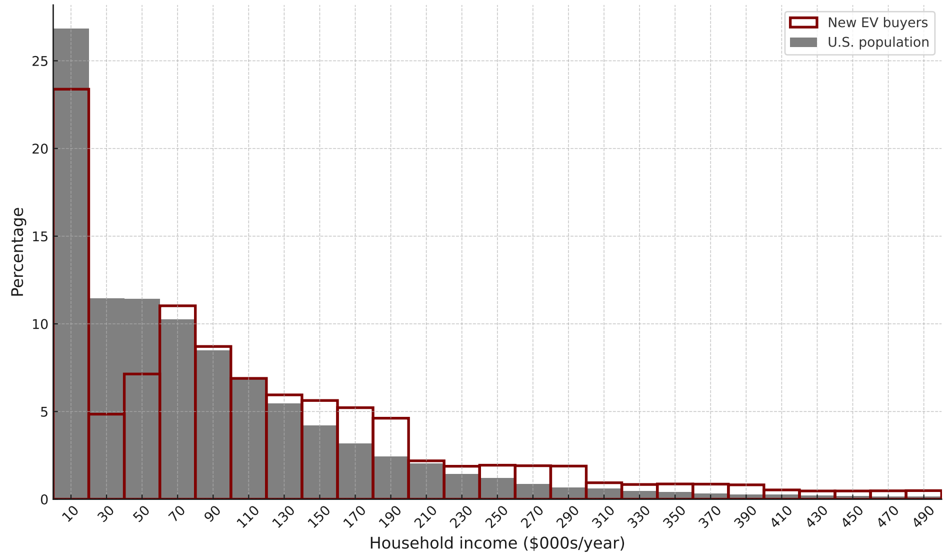
Notes: This figure plots the average load across the hours of a day for vehicles before and after they adopt managed charging.

We further compare how characteristics of the charging events, other than the load shape, change before and after the managed charging adoption. Appendix Figure A7 plots the distributions of the charging duration, charging speed, plug-in time of the charging events, and the number of charging events per vehicle per day. Those distributions seem to remain stable with respect to the timing of managed charging adoption.

3.4 Income Distribution of EV Owners

EV owners are relatively wealthy. As an example illustration, Figure 4 presents the household income distribution of new EV buyers in 2022 and 2023 (in maroon outlines) compared to the U.S. population overall (in grey). The maroon sits well to the right of the grey distribution, illustrating that new EV buyers have higher incomes than the national average. A social planner that places lower social marginal welfare weights on higher-income households would thus likely place less weight on consumer surplus delivered to EV owners.

Figure 4: Income Distribution of EV Buyers



Notes: This figure plots the household incomes of new electric vehicle buyers (in maroon) against the U.S. population overall (in grey). New vehicle buyer incomes are from 2022 and 2023, as recorded in the National Vehicle Experience Survey, a major survey of new vehicle buyers that is fielded by the market research company Strategic Vision and reweighted to address selective non-response. The U.S. population distribution is from the American Community Survey.

4 Empirical Strategy

We exploit the staggered adoption of managed charging at the vehicle level and use a difference-in-differences (DID) strategy to identify the impacts of managed charging adoption on vehicle load shapes. Our analysis uses a balanced panel of charging events across the hours of a day. We denote the vehicle as i, charging event as j, and charging start date as t. Additionally, $h \in \{0,1,2,...,23\}$ represents an hour of a day, and q^h_{ijt} denotes the average energy delivered between hour h and $h+1$ during the charging event j. The empirical model is specified as follows.

$$q^h_{ijt} = \sum_{d=-12,d\neq-2}^{30} \gamma^h_d \mathbb{1}\{t - T_i = d\} + \boldsymbol{X}^h_{it} + \varepsilon^h_{ijt}. \tag{1}$$

The key independent variable is the number of days since the vehicle first adopted managed charging on T_i. Moreover, we include a set of control variables $\boldsymbol{X}_{it}$ to address the potential endogeneity issues in the timing of managed charging adoption. First, we control for the vehicle fixed effects to capture vehicle-specific charging habits. We further interact the vehicle fixed effects with the month-of-sample fixed effects and a weekend indicator (vehicle-by-month-by-weekend fixed effects), to account for the seasonality and within-week cyclicality specific to each driver. Second, we include the charging-start-date fixed effects to capture the common time trend across all vehicles. Third, we control for the total energy delivered for the charge event to isolate load shape changes for events with similar total energy consumption. We allow equation (1) to be fully flexible across hours of a day and all the coefficients are indexed by h.

The identifying assumption is that the load shape of vehicles adopting managed charging would have followed the same trend as non-adopters had they not adopted managed charging. In theory, this could be violated if vehicle owners also made some other change to charging patterns at the same time as they join the program, for example beginning to drive more overall or use public chargers more during the daytime. As we show below, there are no trends in hourly charging load before or after managed charging program adoption, just a sudden change on the day of adoption, so any confounding changes would have to be timed remarkably closely with program adoption.

To summarize the average impact of managed charging adoption on the load shapes, we also estimate an alternative model by replacing the event time dummies $\mathbb{1}\{t-T_i=d\}, d \in [-12,30]$ with a single dummy variable D_{it}, which takes the value one for vehicles after they adopt managed EV charging, and zero otherwise. The empirical model is specified as follows.

$$q_{ijt}^{h} = \gamma^{h} D_{it} + \boldsymbol{X}_{it} + \varepsilon_{ijt}^{h}. \tag{2}$$

Using this model, we further explore the heterogeneity in the effects γ^h across drivers' rate plans, WeaveGrid signal types, and utilities.

Two-way fixed effects models can yield biased estimates in the staggered DID setting when there are heterogeneous treatment effects, as pointed out by the recent literature (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Borusyak et al., 2024). This concern is relevant here because the treatment effects might vary across vehicles under different retail electricity plans and the effects might evolve over time due to vehicle opt-outs or driver override. To address this, we use an imputation-based estimator following Borusyak et al. (2024) as a robustness check. The results are quantitatively similar to those from our main specifications; see Appendix B.

The primary source of variation is the differential timing of managed charging adoption across vehicles. However, since drivers can opt out at any time and managed charging is only available at home, we first examine how adopting managed charging affects the likelihood of charging events being managed. We employ the event study framework as above with an indicator for whether a charging event is managed as the dependent variable. The event study results are shown in Appendix Figure A8. The likelihood of a managed charging event exceeds 80 percent on the first day after adoption, and the likelihood of being managed is stable at 75 percent one month later. For charging events at home, the likelihood of being managed is consistently above 90 percent. Therefore, the managed charging adoption substantially increases the probability of at-home charging events being managed, and the effects are persistent over time.

5 Effects of Managed EV Charging

5.1 Baseline Results

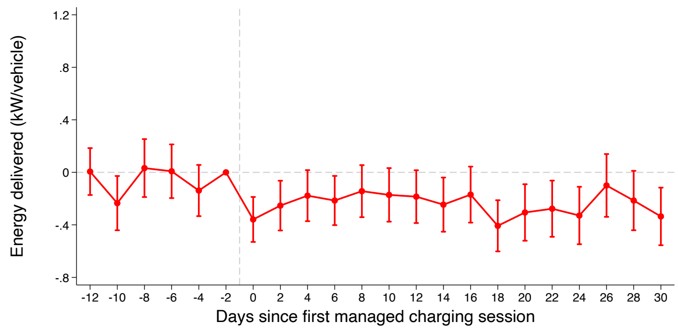
We first estimate the effects of managed charging adoption on hourly load, and the results from the event study are presented in Figure 5. Panel (a) highlights the hour with the largest load decrease (16:00–17:00), while Panel (b) shows the hour with the largest load increase (21:00–22:00). We find that after adopting managed charging, the load between 21:00 and 22:00 has increased by an average of 60 percent, whereas the load between 16:00 and 17:00 has decreased by approximately 20 percent. The absence of significant pre-trends validates our identification assumption, and the effects remain persistent following managed charging adoption. Detailed hourly event study results are provided in Appendix Figures A10 and A11. We find that the hourly load increases between 21:00 and 4:00 the next day, coupled with a persistent and substantial reduction in hourly load between 11:00-13:00 and 16:00-20:00, demonstrating the effectiveness in shifting load across hours of a day by managed charging adoption. Additionally, we notice a sizable reduction in the average load between 5:00 and 6:00, which is mainly due to drivers setting the "charge by" time as 6AM. The WeaveGrid program sets a buffer time to finish charging earlier, mechanically resulting in this reduction.

We next summarize the average effects managed EV charging adoption on hourly load following equation (2), and the results are shown in Figure 6. After adopting managed charging, the average loads between 15:00 and 21:00 have reduced by around 0.2 kW/vehicle, equivalent to 27 percent of the average hourly load without managed charging. The loads are shifted to the window between 21:00 and 4:00. The average loads between 21:00 and 0:00 increase by approximately 0.5 kW/vehicle, which account for 32 percent of the average hourly load without managed charging. The effects further decrease to around 0.2 kW/vehicle between midnight and 4:00, 16 percent of the average hourly load without managed charging.

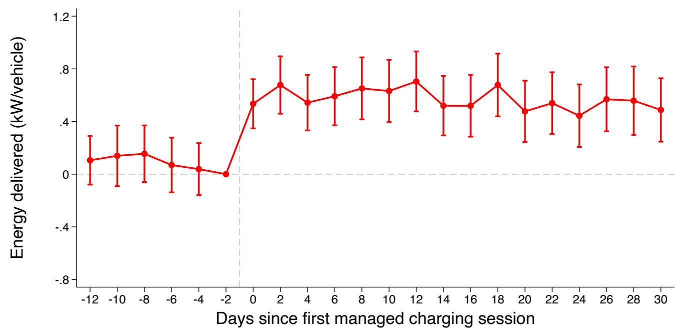
We follow Borusyak et al. (2024) and use an imputation-based estimator to replicate the event studies and the difference-in-differences results. As shown in Appendix Section B, the results are robust and consistent with the main results.

Figure 5: Event Study Estimates of Managed Charging Effects in Two Example Hours

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



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



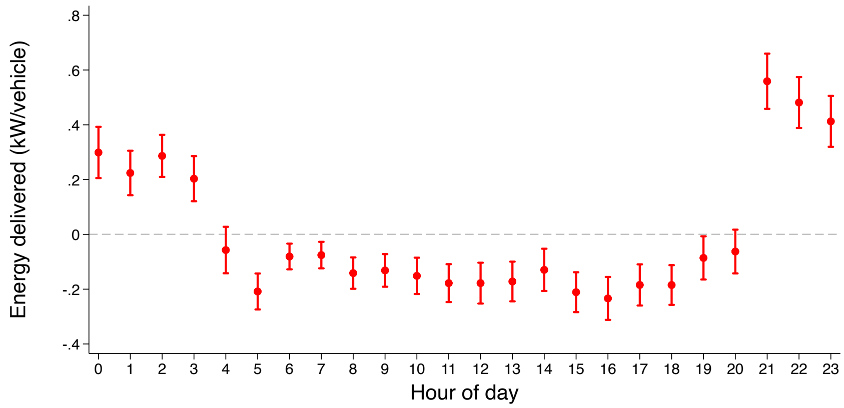
Notes: This figure plots the effects of managed charging on load for two example hours. We present event studies for the two hours with the largest load decrease (Panel (a) for 16:00-17:00) and load increase (Panel (b) for 21:00-22:00). The estimation follows the equation (1). 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

5.2 Effect Heterogeneity

We further examine how the effects of managed charging adoption vary along different dimensions. First, we explore the effect heterogeneity between vehicles on Time-of-Use rate schedules and those on flat rate schedules, highlighting the interaction between rate schedules and managed charging. Second, we examine the heterogeneous effects across charging events under different types of signals. We focus on the two modal signal types: utility price signals, which aims to reducing utilities' total cost of electricity supply, and grid forecast signals, which are designed to mitigate the grid congestion.

The effect heterogeneity between Time-of-Use rate schedules and flat rate schedules is shown in Panel (a) of Figure 7. For vehicles under either rate schedule, we observe a similar reduction

Figure 6: Effects of Managed Charging on Hourly Load Shape



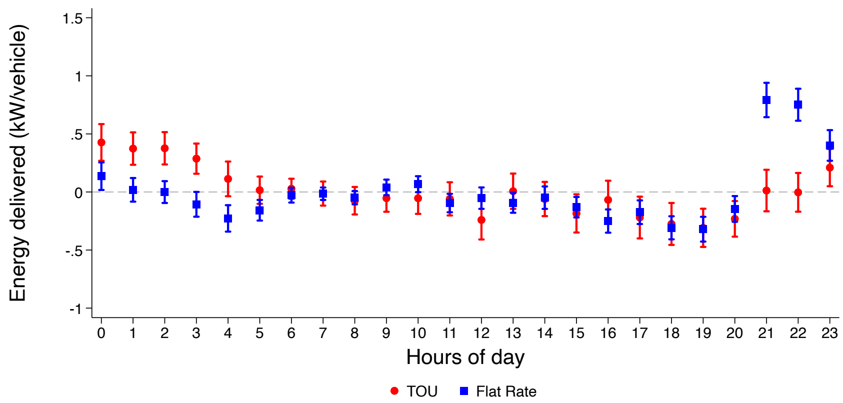
Notes: This figure plots the effects of the managed charging adoption on hourly load shapes. The estimation follows equation (2). 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

in load between 15:00 and 21:00. However, for those vehicles on flat rate schedules, the managed EV charging program tends to shift loads more towards the period between 21:00 and midnight. This is because shifting charging timing will not change the cost to drivers on flat rate schedules, but the cost of electricity supply and the grid congestion will both be lower. For those vehicles on Time-of-Use rate schedules, adopting managed charging results in a more dispersed load shift between 23:00 and 4:00. Since Time-of-Use rate schedules have already shifted average loads towards the period after 21:00, which is a common peak rate end time, dispersing the load shift will be more effective in reducing the congestion rate. This result is consistent with the findings in Bailey et al. (2024b), but further highlighting the additional impact of managed charging *upon* Time-of-Use rate schedules.

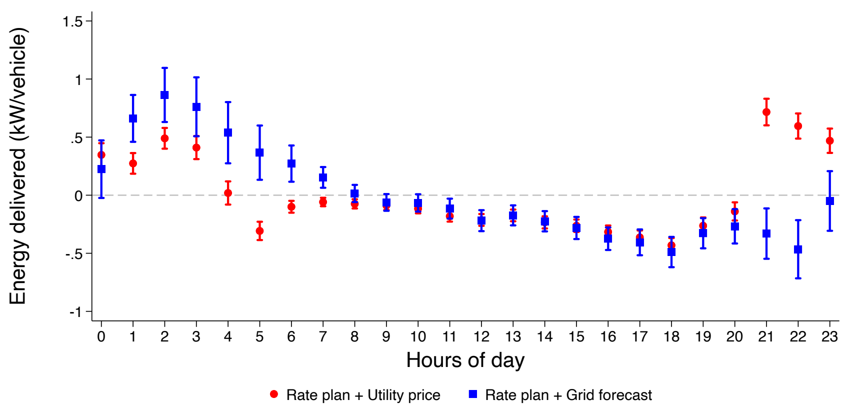
The effect heterogeneity between utility price signals and grid forecast signals is shown in Panel (b) of Figure 7. When the system prioritizes minimizing costs of electricity supply with utility price signals, the load is primarily shifted from the late afternoon and early evening to the period after 21:00. On the other hand, when the system prioritizes smoothing load with grid forecast signals, the load is shifted further into the night, from the late afternoon and evening to after midnight and early morning hours. These results underscore the distinct load shapes under varying optimization goals of the system.

Figure 7: Effect Heterogeneity of Managed EV Charging on Hourly Load Shape

(a) TOU v.s. Flat Rate



(b) Utility Price v.s. Grid Forecast



Notes: This figure plots the heterogeneous effects of the managed charging adoption on the hourly load shapes. Panel (a) plots the effects among vehicles that are under the Time-of-Use rate schedule and the flat rate schedule. Panel (b) plots the effects across charging events under the utility price signals, which target at reducing utilities' total cost of electricity supply, and grid forecast signals, which aim at mitigating the grid congestion.

6 Social Value of Managed EV Charging

6.1 Conceptual Framework and Estimation

In our model, consumers derive utility from energy services (i.e., driving their vehicles) and a numeraire good. We assume that managed charging does not affect utility from energy services, so the value is purely financial. In this draft, we assume that electricity supply is fully elastic, so the hourly wholesale electricity price is exogenous. Thus, managed charging affects surplus by (i) changing consumers' retail electricity costs, (ii) changing utilities' variable profits, and (iii) changing environmental externalities from power plant emissions.

We use q_{it}^h to represent charging load during hour h. p_{it}^h denotes hourly retail electricity price. We use c_{it}^h to represent the hourly wholesale electricity price. $p_{it}^h - c_{it}^h$ measures the unit profit of electricity supply by the utility. ϕ_{it}^h represents the emission externality measured by the hourly marginal rate of emission of CO_2 and local pollutants.

Managed charging shifts hourly load and therefore changes the social value of EV charging. We use $q_{it}^h(1)$ and $q_{it}^h(0)$ to represent potential outcomes for hourly load under managed charging and unmanaged charging, respectively. Since managed charging shifts the charging timing but not the total energy delivered, $\sum_h q_{it}^h(1) = \sum_h q_{it}^h(0)$. Thus, the social value of managed charging is the sum over all hours of the sample of the changes in the driver's electricity costs, the utility's profits, and monetized emissions:

$$V_{it}(1) - V_{it}(0) \approx \underbrace{-\sum_h [q_{it}^h(1) - q_{it}^h(0)] \times p_{it}^h}_{\text{driver's electricity costs}} + \underbrace{\sum_h [q_{it}^h(1) - q_{it}^h(0)] \times (p_{it}^h - c_{it}^h)}_{\text{utility's profit}}$$
$$\underbrace{-\sum_h [q_{it}^h(1) - q_{it}^h(0)] \times \phi_{it}^h}_{\text{environmental externality}}. \tag{3}$$

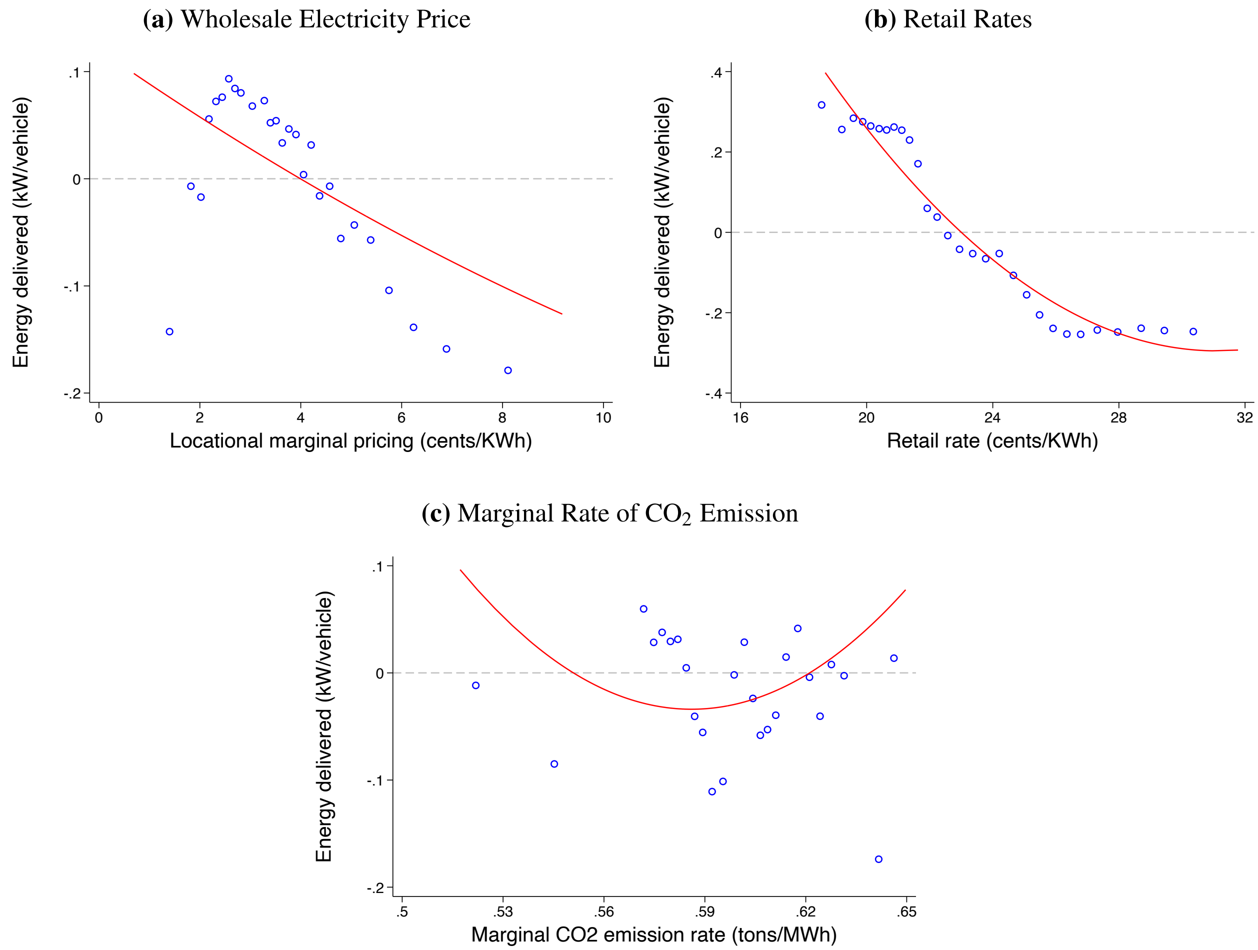
6.2 Quantification of Social Values

To quantify the social value of managed charging as well as the decomposition, we compile additional statistics from various sources. We obtain the hourly locational marginal pricing (LMP) as a measure of wholesale electricity price and the total load from S&P, following Borenstein and Bushnell (2022). Both LMPs and loads are at the hourly level for each ISO/RTO hub where the corresponding utility sits. Moreover, we compile estimates of short-run marginal emission rates from Holland et al. (2024), including the marginal rate of CO_2 and local pollutant emission at the hourly level for each electricity market in the summer and winter, respectively. The retail electricity rate for each charging event window is directly compiled from the data provided by WeaveGrid.

We first estimate the effect of managed charging on hourly load by each utility, since the electricity prices, load, and environmental externality mostly varies at the utility level by hours of a day. The empirical model follows equation (2), and we estimate γ^h separately for each utility. The results are shown in Appendix Figure A12. We assume that the effect of managed charging for each charging event follows the average effect at the hourly level for each utility.

We document the correlation of the load changes with the retail electricity price, wholesale electricity price, and environmental externality, respectively, as shown in Figure 8. We find a strong negative correlation such that the managed EV charging shifts the load away from hours with high retail/wholesale electricity prices to low retail/wholesale electricity prices. However, we don't find a strong relationship between load changes and marginal environmental externalities.

Figure 8: Correlation between the Treatment Effects, Electricity Rates, and Emission Rates



Notes: This figure plots the correlation between the treatment effects, the electricity rates, and the marginal rate of CO_2 emission across different hours of the day. Panel (a) plots the correlation between the treatment effects and the hourly wholesale electricity prices. Panel (b) plots the correlation between the treatment effects and the hourly retail electricity rates. Panel (c) plots the correlation between the treatment effects and the hourly marginal rate of CO_2 emission.

The social value change is summarized in Table 1. Under unmanaged charging, drivers on average pay $6 per day of charging and utilities could pay $1 on average for the electricity generation. Managed EV charging reduces electricity expenditures for EV drivers by about $60 per year per vehicle, or about 2.6 percent of the unmanaged charging cost. Utilities' electricity generation cost falls by about $12 per year per vehicle, or about 2.9 percent of the value under unmanaged charging. There are only marginal effects on environmental externalities—only a decrease of 1 dollar per year per vehicle. On net, total surplus increases by around $15 per year per vehicle.

In the short run, with fixed retail electricity prices, managed EV charging shifts surplus from utility profits to managed charging program participants. In the longer run, regulators will generally allow utilities to raise prices to maintain their regulated rate of return. Thus, managed EV charging will shift surplus from all ratepayers to the EV owners who participate in the program. As shown above, these EV owners are relatively wealthy.

Table 1: The Distributional Effects and Social Value of Managed Charging

	Unmanaged	Managed	Difference	Percentage Change
	dollars/vehicle-day			%
Drivers' cost of charging	6.11	5.95	-0.16	-2.62
Utilities' cost of electricity supply	1.04	1.01	-0.03	-2.88
Utilities' profit	5.07	4.94	-0.13	-2.56
Environmental externality	-1.83	-1.82	0.01	-0.54
Social value	-	-	0.04	-

Notes: This table presents the distributional effects and social value of managed EV charging.

We re-emphasize two important caveats of the current benefit and cost analysis. First, our quantification leaves out one important aspects of the benefits brought by managed charging, which is the delay of local transformer degradation. This quantification is challenging and calls for more detailed data on the hourly load shape at the transformer level, and is under work in progress. We plan to follow Powell et al. (2020) to quantify how managed charging saves the infrastructure replacement cost in the next step. Second, our quantification exercise assumes that the wholesale electricity price is exogenous with respect to the charging load, which is justified by a limited sample of EVs. However, allowing the wholesale electricity price to respond will be an important aspect to incorporate if we extrapolate our estimates to future EV growth.

7 Conclusion

This paper evaluates the impacts of managed charging on the hourly load as well as its social values. We exploit a proprietary EV charging data sets covering around 27,000 vehicles at a 15-minute frequency, and use a difference-in-differences strategy to examine the impacts of managed charging adoption at the vehicle level. We document an effective load shift from the daytime to after 21:00 after managed charging adoption. Managed charging saves the charging expenditure by for drivers by approximately 2.7 percent, saves the cost of electricity supply by about 3.1 percent for utilities, and improves social surplus by 15 dollars per year per vehicle.

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Online Appendix

Hunt Allcott Luming Chen

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B Event Study with Imputation-based Estimator **A4**

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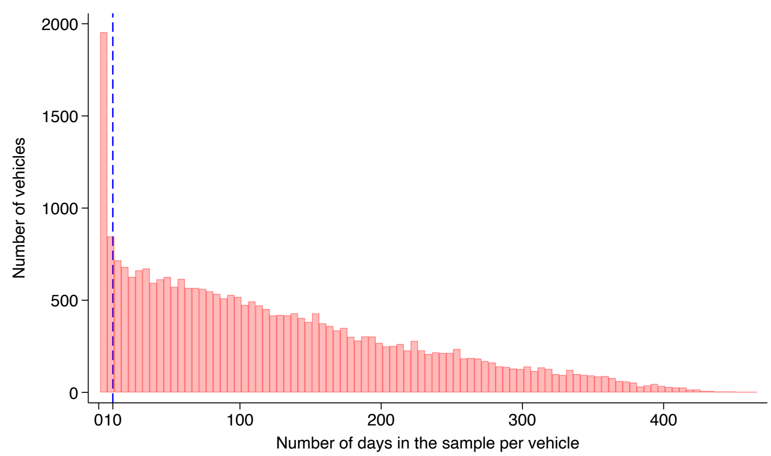
A Data Cleaning

A.1 Days in the Sample

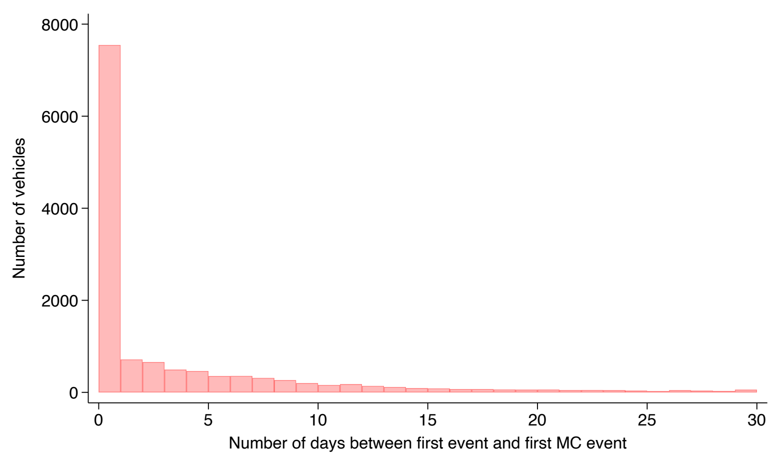
We first plot the number of days in the sample for each vehicle in Panel (a) of Figure A1. Vehicles on average have 123 days in the sample. However, 2.5 percent of the vehicles only have one day of observations in the sample, and 9.8 percent of the vehicles have fewer than 10 days of observations in the sample. To ensure enough coverage for each vehicle, we dropped vehicles that have fewer than 10 days of observations from the sample.

Figure A1: Number of Days across Vehicles

(a) Number of Days in the Sample



(b) Number of Days before First Managed Session Per Vehicle



Notes: This figure plots the distribution of the number of days across vehicles. Panel (a) plots the the number of days in the sample per vehicle. Panel (b) plots the distribution of the number of days in the sample before the first managed charging session across vehicles. We truncate the distribution and only keep vehicles with fewer than 30 days in the sample before the first managed session.

Panel (b) of Figure A1 plots the distribution of the number of days in the sample before the first managed charging session for those vehicles that have been managed. The average gap between the first day in the sample and the first managed charging session for each vehicle is 13 days, while 53.8 percent of the vehicles are managed in the first session in the sample. As we exploit the staggered adoption of the managed charging adoption at the vehicle level, those vehicles that are always managed constitutes the "forbidden" comparison group and thus are dropped from the sample. Moreover, we limit the sample to vehicles that have at least five days between the first session in the sample and the first managed charging session. We have 14,455 vehicles and approximately 1.7 million charging events remaining in the sample.

A.2 Utilities in the Sample

We summarize the number of vehicles across 17 utilities in the sample in Table A1. We calculate the total number of vehicles as well as its decomposition into four different groups, including vehicles that are always managed, vehicles that have been managed with the gap between the first day in the sample and the first managed charging session fewer than 5 days, vehicles that have been managed with the at least five days before the first managed charging session, and vehicles that are never managed. Since the vehicles that are always managed constitutes the "forbidden" comparison group in the staggered difference-in-differences design, we drop this group from the sample. To ensure a pre-treatment period long enough, we drop the vehicles that have been managed with the gap between the first day in the sample and the first managed charging session fewer than 5 days. Therefore, the last two columns in the table constitutes our final sample. We keep utilities with balanced numbers of vehicles that have adopted the managed charging program and those that have not, including utility 2, 3, 4, 5, 7, 8, 9, 13, 24, 36, 58, 129, and 133.

Table A1: Number of Vehicles by Utility

Utility ID	Total Number	Always MC	Ever MC < 5 pre days	Ever MC 5+ pre days	Never MC
2	6,609	2,280	922	800	2,607
3	1,687	617	82	617	371
4	304	67	8	41	188
5	3,314	303	47	605	2,359
7	2,786	1,496	360	421	509
8	4,675	2,200	254	362	1,859
9	439	213	15	13	198
13	1,278	78	110	791	299
15	423	0	0	0	423
24	440	55	162	49	174
36	427	31	60	161	175
57	32	11	10	7	4
58	948	83	208	134	523
129	171	8	27	79	57
130	170	0	0	0	170
131	138	0	0	0	138
133	323	100	63	83	77

Notes: This table summarizes the number of vehicles by utilities. We tabulate the total number of vehicles observed in each utility (column "Total Number") as well as its decomposition into the following four groups: (1) the number of vehicles that are always under the managed charging (column "Always MC"); (2) the number of vehicles that have ever been managed with fewer than five days in the sample before the first managed session (column "Ever MC < 5 pre days"); (3) the number of vehicles that have ever been managed with at least five days in the sample before the first managed session (column "Ever MC 5+ pre days"); (4) the number of vehicles that are never under the managed charging (column "Never MC").

B Event Study with Imputation-based Estimator

We exploit a Two-Way Fixed Effects (TWFE) model to examine the impacts of managed charging adoption on vehicle load shapes and use an imputation-based estimator following Borusyak et al. (2024) as a robustness check. Similar to the main specification, we use i, j, and t to denote the vehicle, charging event, and charging start date, respectively, with $h \in \{0, 1, 2, ..., 23\}$ representing the hour of the day. The variable q^h_{ijt} denotes the average energy delivered between hour h and $h+1$ during charging event j. Vehicle i adopts the managed charging program on date T_i. If a vehicle i never adopts managed charging during the sample period, we set $T_i = \infty$. We define $q^h_{ijt}(0)$ as the *potential outcome* if the vehicle have not adopted managed charging. For vehicles that have never adopted managed charging or have not yet adopted it, we assume $q^h_{ijt} = q^h_{ijt}(0)$. The *potential outcome* $q^h_{ijt}(0)$ is parameterized as follow.

$$q^h_{ijt}(0) = \delta^h_i \kappa_t + \gamma^h_t + \beta^h x_j + \varepsilon^h_{ijt}. \tag{4}$$

$q^h_{ijt}(0)$ depends on the interactions between the vehicle fixed effect δ^h_i and a weekday indicator κ_t. Moreover, $q^h_{ijt}(0)$ depends on the charging date fixed effects γ^h_t, the total energy delivered during the charging event x_j, as well as a random shock ε^h_{ijt}. We allow equation (4) to be fully flexible across hours of the day and all the coefficients are indexed by h. Following Borusyak et al. (2024), the treatment effects of managed charging adoption is defined as $\tau^h_{ijt} = E[q^h_{ijt} - q^h_{ijt}(0)]$, and the average treatment effects is aggregated using non-stochastic weights depending on the treatment status and the timing.

The estimation of the average treatment effects involves three steps. We first estimate equation (4) with OLS on the sample of vehicles that never adopt managed charging or haven not yet adopted it. Second, we estimate the treatment effect for each vehicle in each hour using $\hat{\tau}^h_{ijt} = q^h_{ijt} - \hat{q}^h_{ijt}(0)$ with$\hat{q}^h_{ijt}(0)$ estimated from the first step. Third, we aggregate the estimated treatment effects using the sample weight. The full event study estimate τ_h is defined as below.

$$\tau_d = \sum_{ijt \in \Omega_d} \omega_{ijt} \hat{\tau}^h_{ijt}, \quad \omega_{ijt} = \frac{\mathbb{1}(t - T_i = d)}{|\Omega_d|} \quad \text{for} \quad \Omega_d = \{ijt : t - T_i = d\}.$$

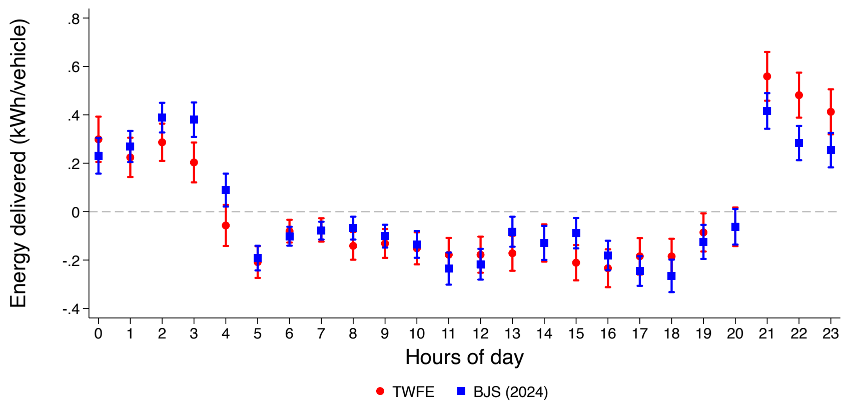
We group vehicles and days according to the number of dates since the adoption of the managed charging program, denoted as d. We examine the coefficient of τ_d between 12 days before the managed charging adoption and 30 days after that.

The average treatment effect τ is defined as below.

$$\tau = \sum_{ijt \in \Omega} \omega_{ijt} \hat{\tau}^h_{ijt}, \quad \omega_{ijt} = \frac{\mathbb{1}(t \geqslant T_i)}{|\Omega|} \quad \text{for} \quad \Omega = \{ijt : t \geqslant T_i\}.$$

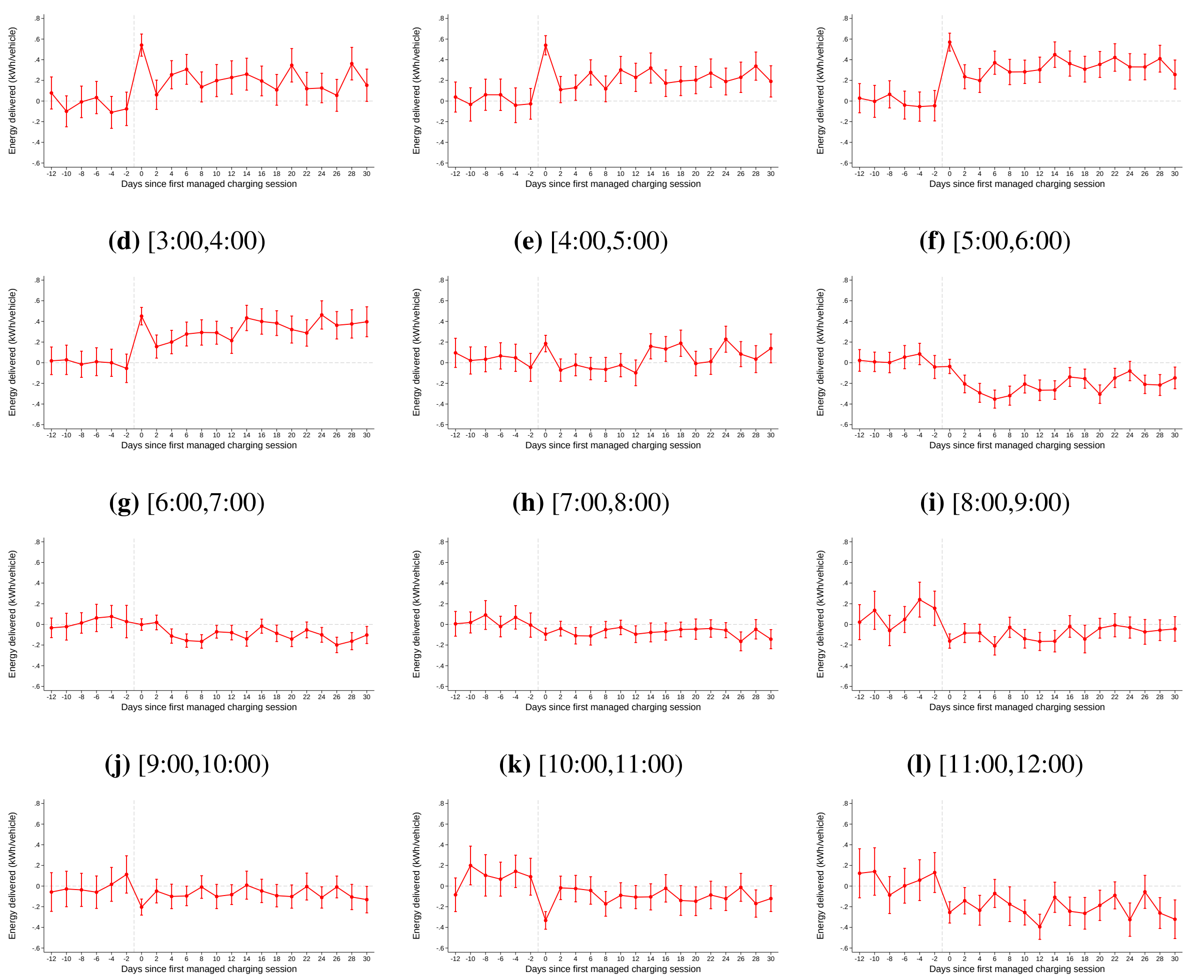
The full event study results following Borusyak et al. (2024) are shown in Figures A3 and A4, which are quantitatively similar to the event study results using TWFE. We plot the estimated average effects on the hourly load using the TWFE model and the imputation-based estimator in Figure A2. The two sets of estimates exhibit similar hourly patterns. TWFE estimates are larger between 21:00 and 0:00 than the imputation-based estimates and smaller between 2:00 and 4:00.

Figure A2: Comparison between TWFE Estimates and Imputation-based Estimates



Notes: This figure compares the estimated effects of MC on he average hourly load using TWFE model and Borusyak et al. (2024). The estimation results from the TWFE model follows equation (2) and the estimation results following Borusyak et al. (2024) is discussed in detail in Appendix Section B. 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

Figure A3: The Effects of Managed Charging on Hourly Load (AM, Imputation-based)



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

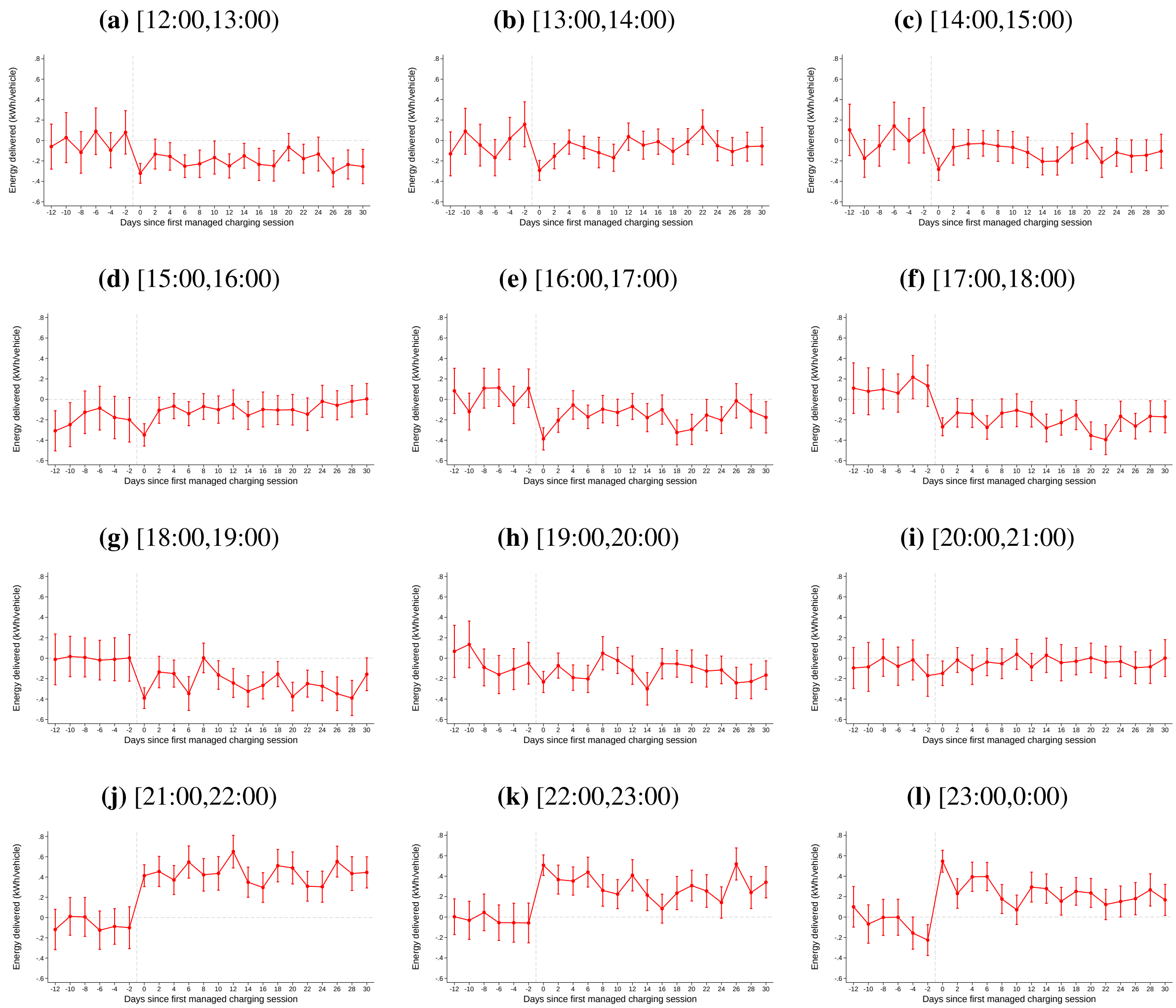
(d) [3:00,4:00) **(e)** [4:00,5:00) **(f)** [5:00,6:00)

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

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

Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 am and 12:00 pm. The estimation follows Borusyak et al. (2024) and is discussed in detail in Appendix Section B. 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

Figure A4: The Effects of Managed Charging on Hourly Load (PM, Imputation-based)

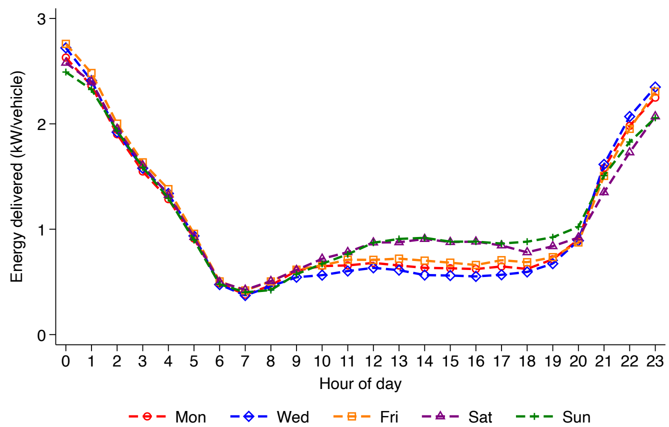


Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 pm and 0:00 am (on the next day). The estimation follows Borusyak et al. (2024) and is discussed in detail in Appendix Section B. 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

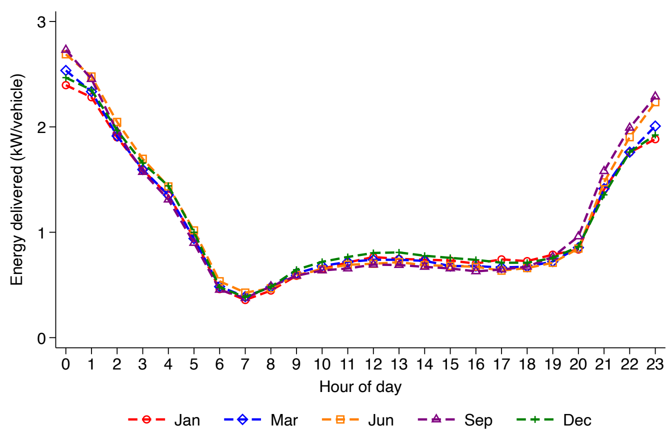
C Additional Figures and Tables

Figure A5: Load Shape for Never-Managed Vehicles across Days and Months

(a) Days of the Week

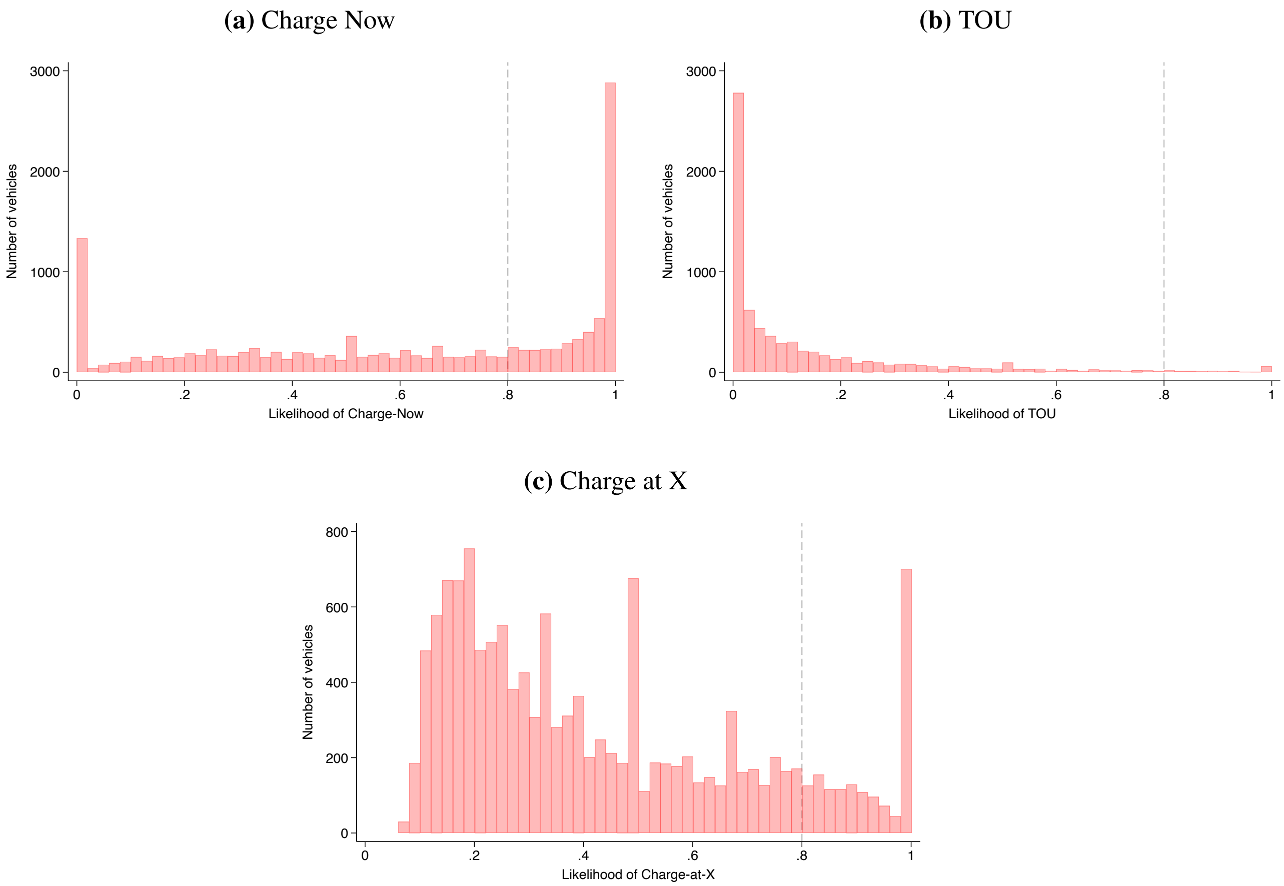


(b) Months



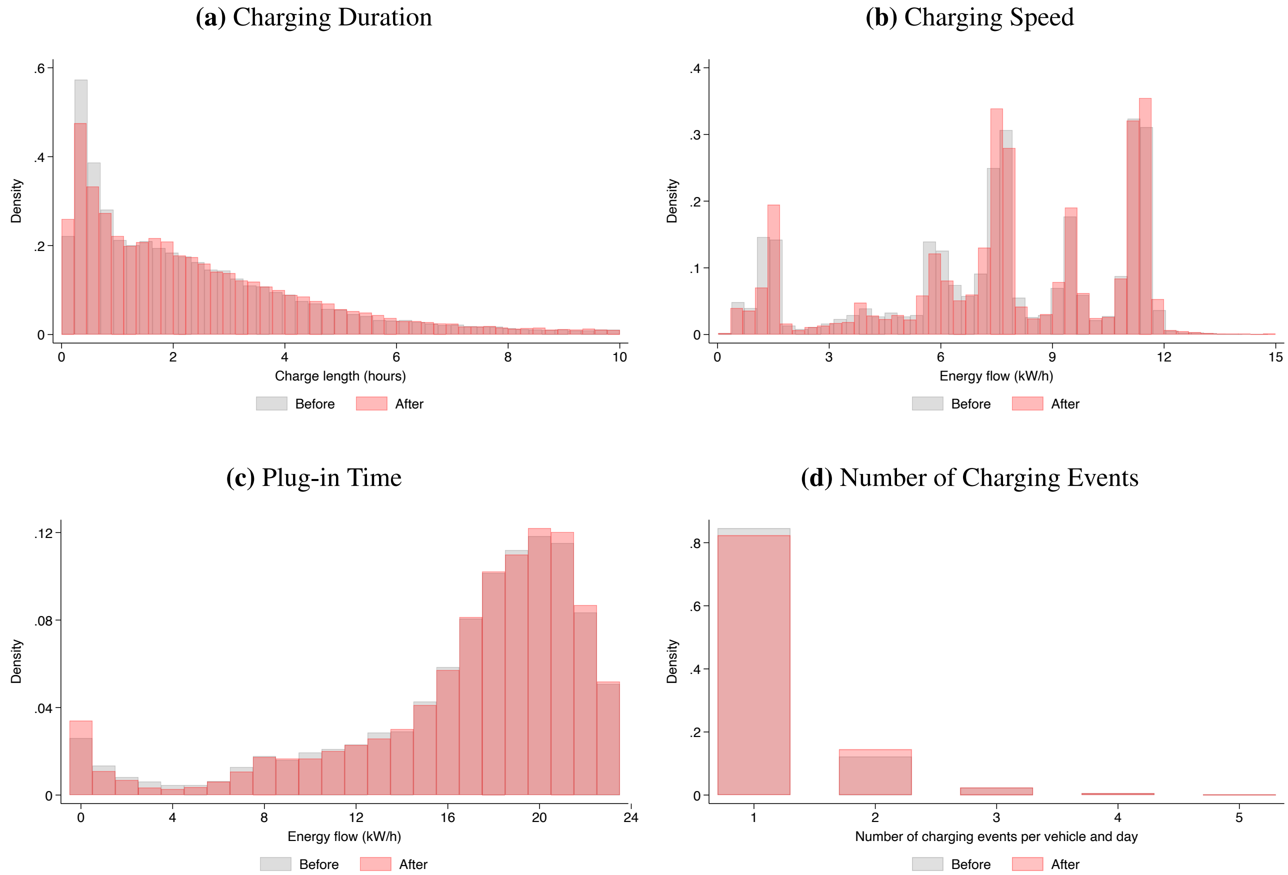
Notes: This figure plots the average load shape across hours of a day for vehicles that are never under the managed charging during the sample window. Panel (a) plots the average load shape by day of a week. Panel (b) plots the average load shape by month.

Figure A6: Load Shape for Never-Managed Vehicles



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

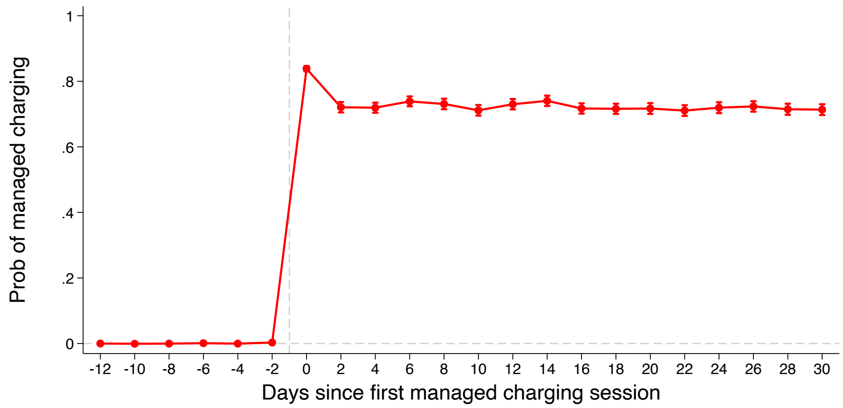
Figure A7: Before-after Comparison of Other Charging Characteristics



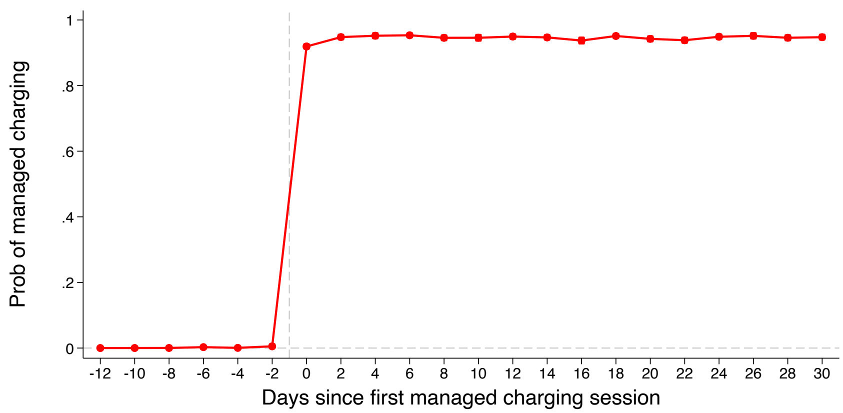
Notes: This figure compares three characteristics of charging events before and after the vehicles adopt the managed charging program. Panel (a) plots the distribution of the durations of the charging events, Panel (b) plots the distribution of the durations of the charging speed, Panel (c) plots the distribution of the plug-in time, and Panel (d) plots the distribution of the number of charging events per vehicle and day.

Figure A8: Probability of Charge Events Being Managed

(a) Charge Events Being Managed

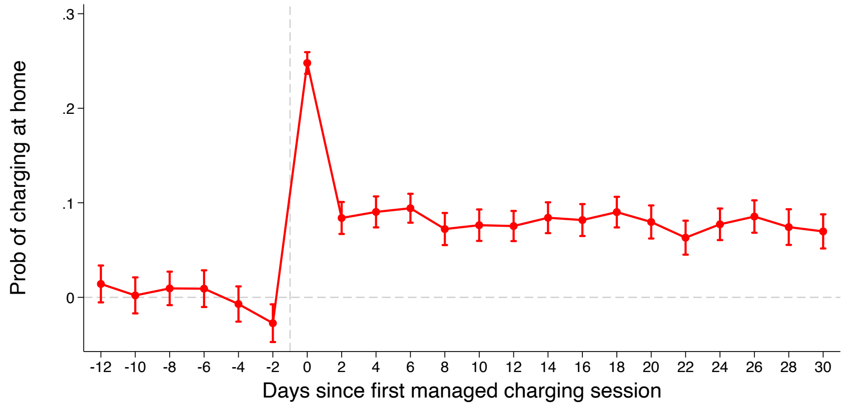


(b) At-home Charge Events Being Managed



Notes: This figure plots the effects of the managed charging adoption on the likelihood of the charging events being managed. Panel (a) examines the impacts on the likelihood of having the charging events managed, and Panel (b) further restricts the sample to the charging events at home. The estimation follows Borusyak et al. (2024) and is discussed in detail in Section (4). 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

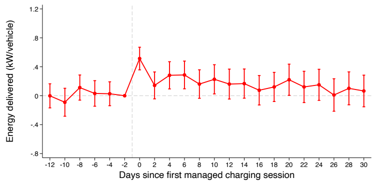
Figure A9: Probability of Charging at Home



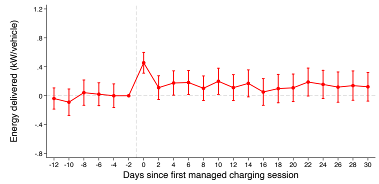
Notes: This figure plots the effects of the managed charging adoption on the likelihood of the charging events being at home. The estimation follows Borusyak et al. (2024) and is discussed in detail in Section (4). 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

Figure A10: The Effects of Managed Charging on Hourly Load (AM, TWFE)

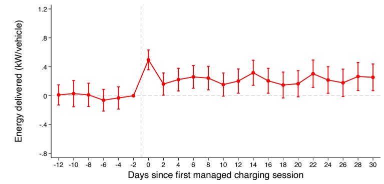
(a) [0:00,1:00)



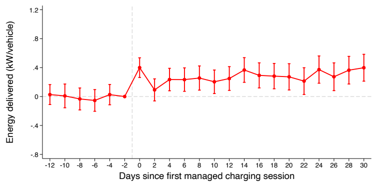
(b) [1:00,2:00)



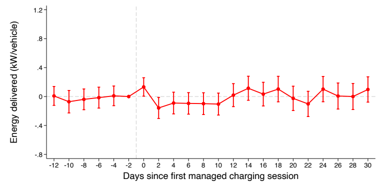
(c) [2:00,3:00)



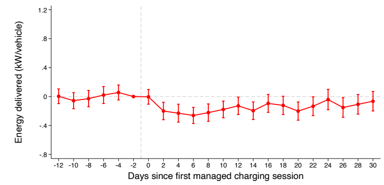
(d) [3:00,4:00)



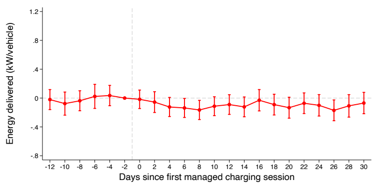
(e) [4:00,5:00)



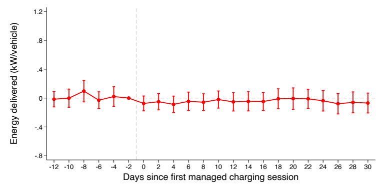
(f) [5:00,6:00)



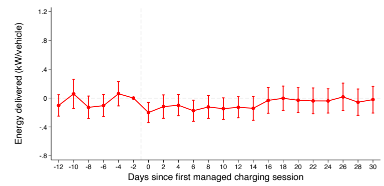
(g) [6:00,7:00)



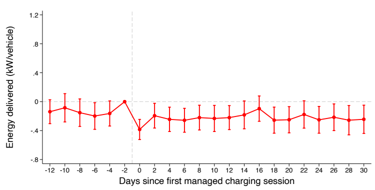
(h) [7:00,8:00)



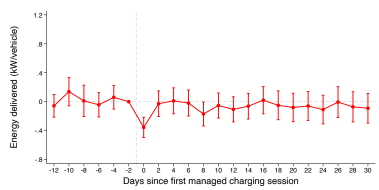
(i) [8:00,9:00)



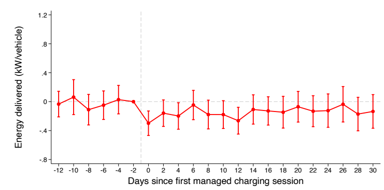
(j) [9:00,10:00)



(k) [10:00,11:00)



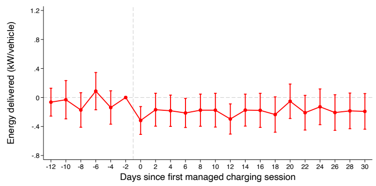
(l) [11:00,12:00)



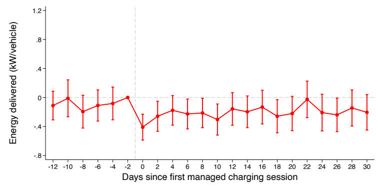
Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 am and 12:00 pm. The estimation uses the TWFE model and follows equation 1. 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

Figure A11: The Effects of Managed Charging on Hourly Load (PM, TWFE)

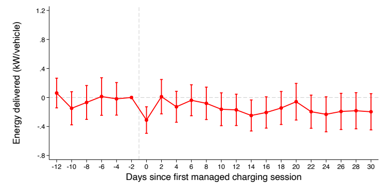
(a) [12:00,13:00)



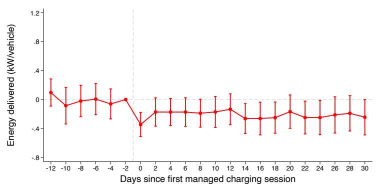
(b) [13:00,14:00)



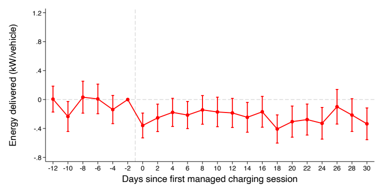
(c) [14:00,15:00)



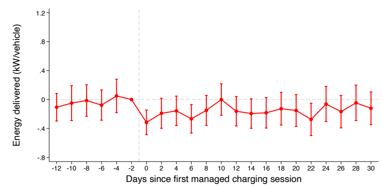
(d) [15:00,16:00)



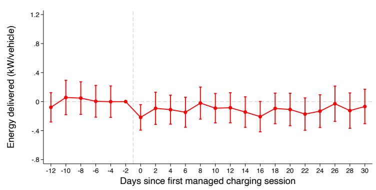
(e) [16:00,17:00)



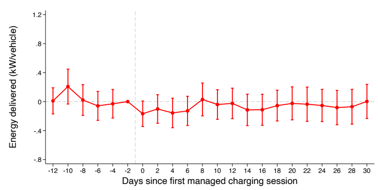
(f) [17:00,18:00)



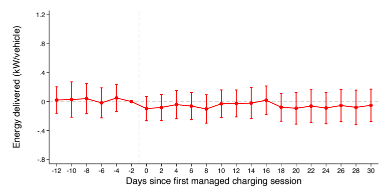
(g) [18:00,19:00)



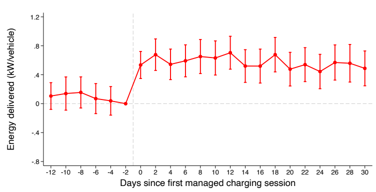
(h) [19:00,20:00)



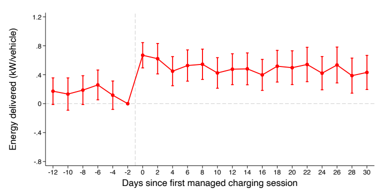
(i) [20:00,21:00)



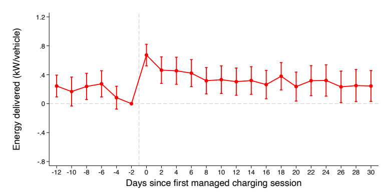
(j) [21:00,22:00)



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

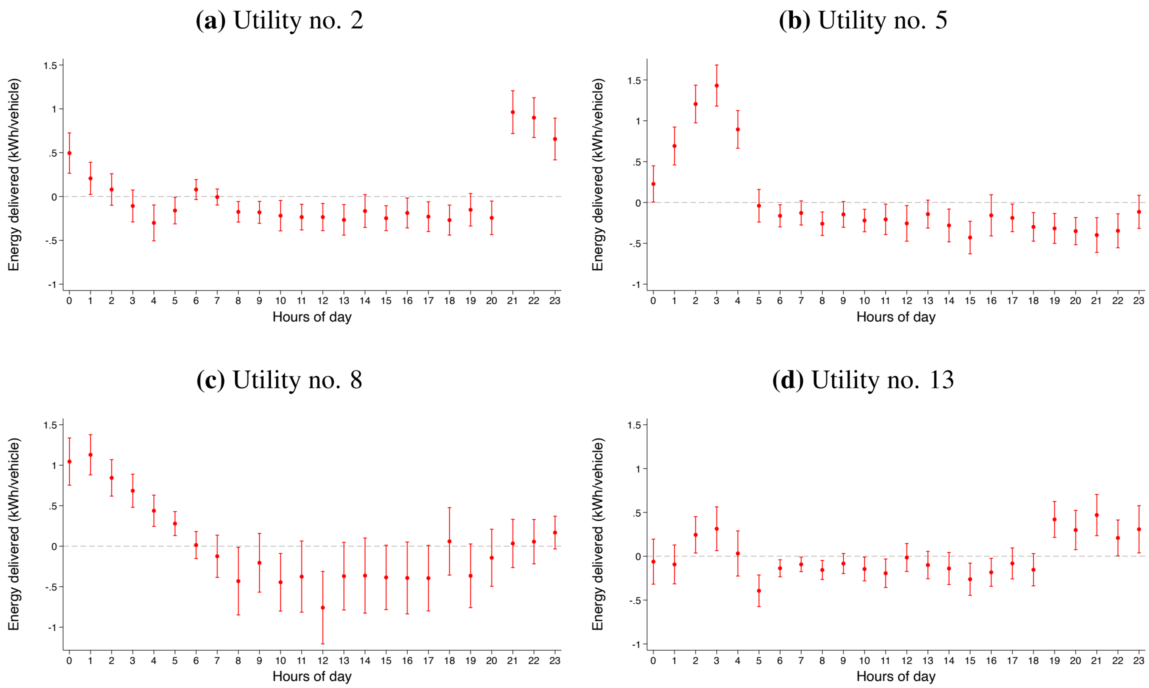


(l) [23:00,0:00)



Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 pm and 0:00 am. The estimation uses the TWFE model and follows equation 1. 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

Figure A12: Effect Heterogeneity of Managed EV Charging on Hourly Load across Utilities



Notes: This figure plots the heterogeneous effects of managed charging adoption on the hourly load across four largest utilities in the sample. Names of utilities are anonymized per data agreement. The estimation uses the TWFE model and follows equation 1 for each utility separately. 95% confidence intervals are plotted with standard errors clustered at the vehicle level.