Measuring the Social Value of Managed EV Charging

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Abstract

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. Overall, managed charging saves the charging expenditure by approximately 2.7 percent for drivers, 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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1 Introduction

Electric vehicles (EVs) are experiencing rapid growth in the United States, driven by government incentives, advancements in battery technology, and improvements in charging infrastructure. Although EVs provide environmental benefits as they reduce greenhouse gas emission by the replacement of gasoline-power vehicles, 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. Moreover, higher electricity prices might increase costs for both utilities and drivers. One solution to address these concerns is to implement managed EV charging, a new technology optimizing EV charging time to balance rapid EV growth with the need for a stable and cost-efficient electricity grid.

Managed charging is implemented by utilities to recruit drivers and strategically manage when and how the electric vehicles are charged without compromising the operational needs. Despite the prospects of managed charging, empirical evidence is scarce about how effective managed charging is in shifting the EV charging load, with the exception of Bailey et al. (2024b) using the lab experiment. This paper provides the first empirical study using large-scale managed charging programs. We collaborate with WeaveGrid, a leading managed charging program provider, and access proprietary EV charging data from 27,000 vehicles and 17 utilities at 15-minute frequency in June 2023 - September 2024. We exploit the staggered adoption of managed charging at the vehicle level and employ a difference-in-differences strategy to to identify the impacts of managed charging adoption on vehicle loads.

Our empirical analysis takes three steps. First, we provide a set of novel descriptive evidence on how drivers charge their vehicles if unmanaged. We find that more than 70 percent of the charging events happen at home, and 64.2 percent of the charging load occurs delivered between 21:00 and 6:00 the next day. Charging events at home and away from home exhibit distinct patterns within a day: energy consumption for charging events at home peak between 21:00 and 6:00 the next day, while energy consumption for charging events away from home peak between 9:00 and 17:00. Vehicles are also on two main types of retail rate schedules: Time-of-use (TOU) schedule and flat rate schedule. We find that Time-of-use pricing tends to shift the load away between 15:00 and 21:00 to after the midnight, compared with that on flat rate schedule.

Second, we estimate how managed charging shifts hourly load with an event study framework. We mainly exploit the differential timing of managed charging adoption across vehicles to identify the impacts of managed charging. The identification 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. There are several challenges to the plausibility of this assumption. For example, drivers who adopt managed charging earlier may be more cost-conscious or environmentally aware. Moreover, local grid experiencing more severe congestions during peak hours might promote managed charging programs. We address these identification concerns by adding a rich set of controls, including the vehicle-by-month fixed effects and charging date fixed effects. We further validate the identification assumption by examining pre-trends in the event study results. To address the concerns of negative weights in the canonical two-way fixed effects models, we use an imputation-based estimator following Borusyak et al. (2024) as a robustness check.

We find that after adopting managed charging, 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. After adopting managed charging, the average loads between 15:00 and 21:00 have reduced by around 0.2 MWh/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 MWh/vehicle, which account for 32 percent of the average hourly load without managed charging. The effects further decrease to around 0.2 MWh/vehicle between 0:00 and 4:00, 16 percent of the average hourly load without managed charging.

The effects of managed charging adoption also exhibit heterogeneity along different dimensions. First, we find that for those vehicles on flat rate schedules, the managed EV charging program tends to shift loads more towards the period between 21:00 and 0:00. 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. Moreover, 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. 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.

Third, we quantity social values of managed charging, incorporating the the cost savings to drivers and utilities, the environmental externality, as well as the wholesale price responses. We find a strong negative correlation such that managed charging shifts the load away from hours with high retail/wholesale electricity prices to low retail/wholesale electricity prices. However, we don't find clear relationship between the load changes and environmental externality. Overall, the managed EV charging saves the cost for EV drivers by about 60 dollars per year per vehicle by approximately 2.7 percent, while the electricity generation cost of utilities would fall by about 12 dollars per year per vehicle by about 3.1 percent. The impacts on the environmental externality is marginal, only a decrease of 1 dollar per year per vehicle. On net, the social value per year per vehicle increases by around 15 dollars. Consequently, the managed EV charging shifts the utility profit to the cost saving of consumers, and on average improves the social value of EV charging.

Our research contributes to the following strands of the literature. First, this paper adds to the literature on the evaluation of managed charging program. Bailey et al. (2024b) is the most related work, in which the authors implement a field experiment to evaluate how the time-of-use schedules and managed charging shape drivers' charging behavior. Compared to Bailey et al. (2024a), our paper focused 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 interactive consequences of both programs, advancing the side-by-side comparison in Bailey et al. (2024a). There are 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 provide 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, and 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 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 upgrade. Moreover, evening peak hours often correspond to the highest wholesale electricity prices, as well as retail rates for vehicles on the 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),

[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.

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

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 ($100) 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 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.

3 Data and Descriptive Evidence

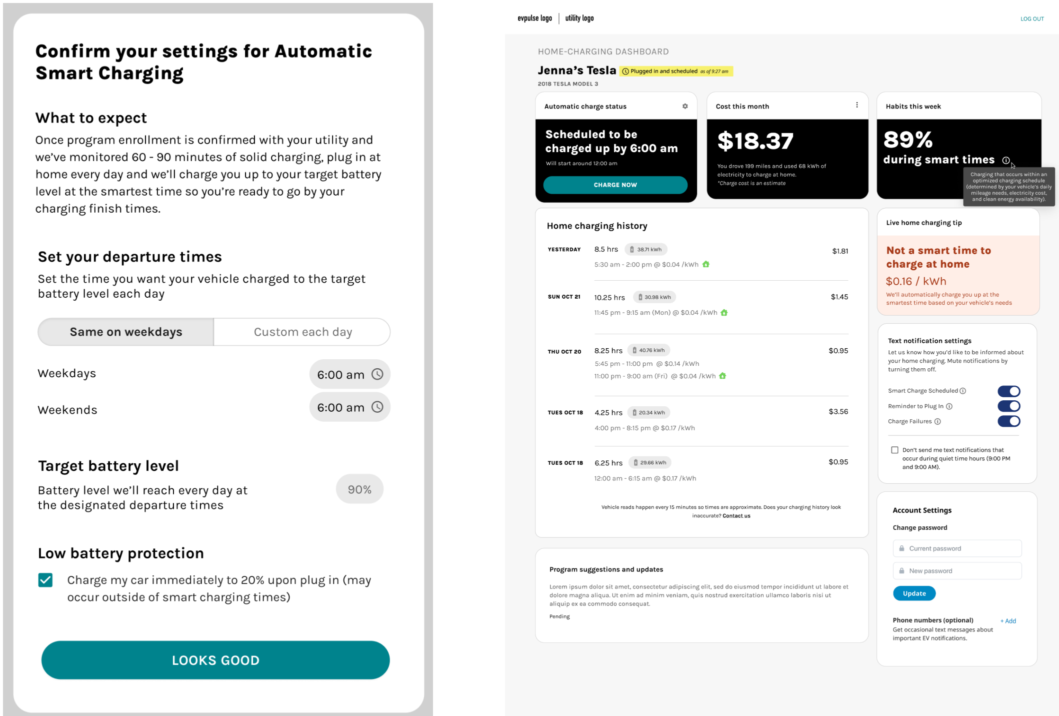
3.1 Data

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

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

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.

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 23.9 kWh on an average charging day, 64.2 percent of which is delivered between 21:00 and 6:00 (on the next day), and 35.8 percent of which is delivered between 6:00 and 21:00. Among all the charging events, 73.3 percent occur at home, which constitutes 69.2 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.

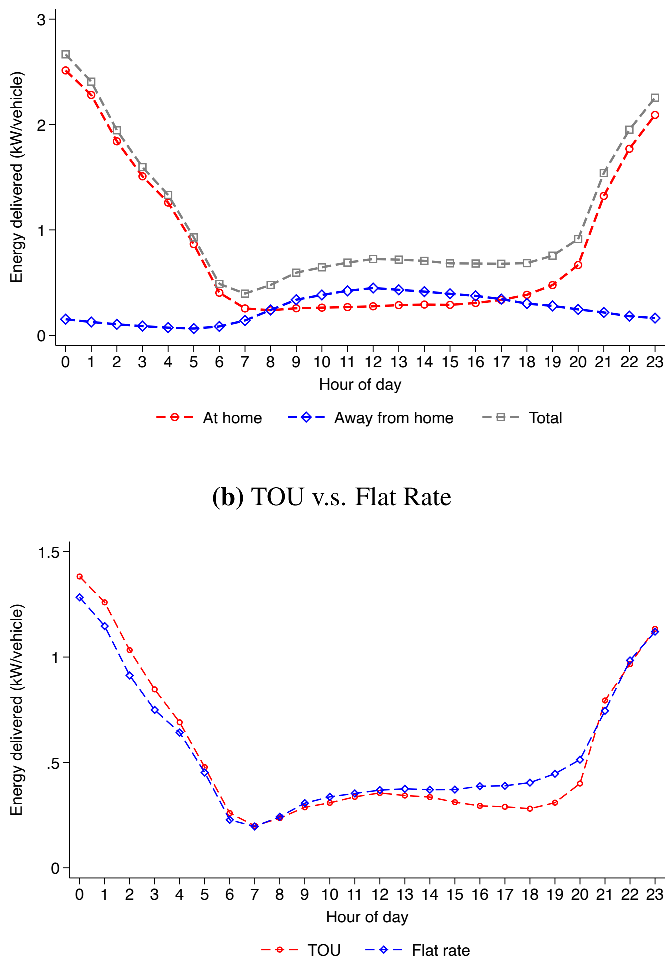
Moreover, 52.0 percent of the charging events are under the time-of-use (TOU) pricing. Although the load shapes for charging events under the time-of-use (TOU) pricing and flat rate schedule are similar, we find that the TOU pricing tends to shift the load away between 15:00 and 21:00 to after the midnight. Consequently, the total energy delivered between 15:00 and 21:00 is lower by 25.0 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

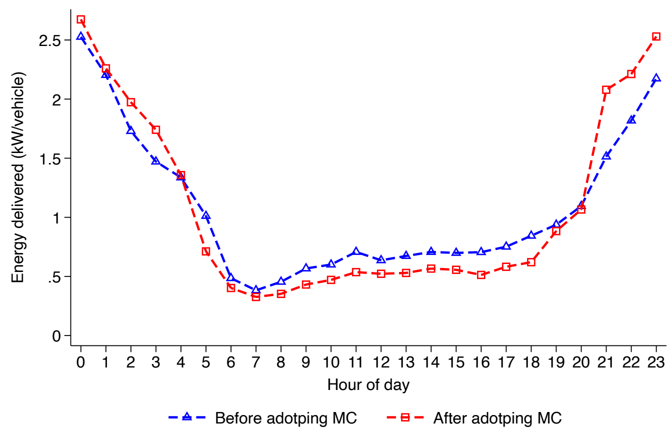


Notes: This figure illustrates the average load across the hours of a day for vehicles that are never managed during the sample period. Panel (a) presents the average load, further decomposed into home charging and away-from-home charging. Panel (b) provides a breakdown of the average load based on charging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

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.

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

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 the 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 identification 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. There are several challenges to the plausibility of this assumption. First, drivers who adopt managed charging earlier may be more cost-conscious or environmentally aware. By including vehicle fixed effects, we compare load shape changes within the same driver before and after adoption, alleviating concerns about this bias. Second, local grid experiencing more severe congestions during peak hours might promote managed charging programs. This is addressed by the vehicle fixed effects specific to an hour of a day. Third, drivers that have been in other EV charging incentive programs (e.g., Time-of-Use rate plans) or gained access to local public charging facilities might be less likely to adopt managed charging. We control for this by including the vehicle-by-month fixed effects. We further validate the identification assumption by examining pre-trends in the event study results.

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.

$$q^h_{ijt} = \gamma^h D_{it} + \boldsymbol{X}_{it} + \varepsilon^h_{ijt}. \tag{2}$$

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

However, the canonical two-way fixed effects models could 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 discussed in the Appendix B and quantitatively similar to those from our main specifications.

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 4. 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 6:00 am. 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 5. After adopting managed charging, the average loads between 15:00 and 21:00 have reduced by around 0.2 MWh/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

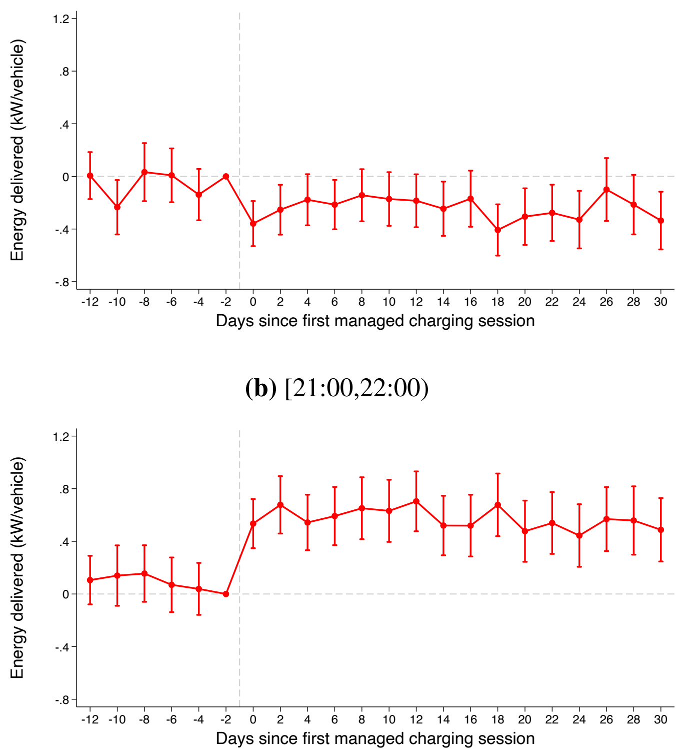
MWh/vehicle, which account for 32 percent of the average hourly load without managed charging. The effects further decrease to around 0.2 MWh/vehicle between 0:00 and 4:00, 16 percent of the average hourly load without managed charging.

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 4: Effects of Managed Charging on Hourly Load

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

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

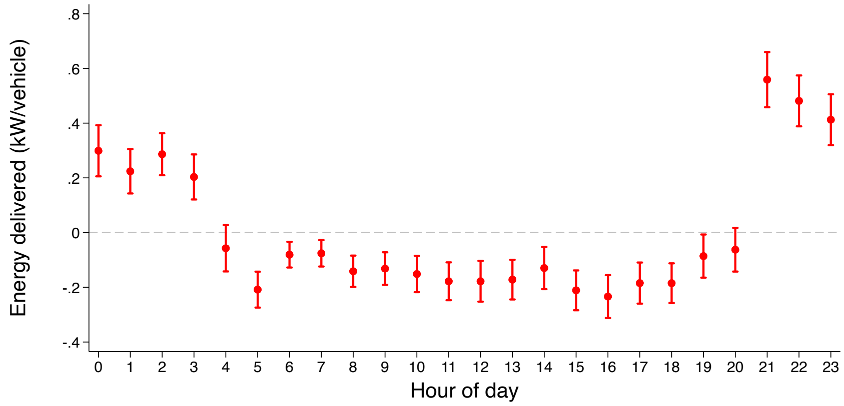


Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for two hours with the largest load decrease (Panel (a) for 16:00-17:00) and load increase (Panel (b) for 21:00-22:00). The estimation follows the equation (1). 95% confidence intervals are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

Figure 5: Effects of Managed Charging on the Load Shape



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

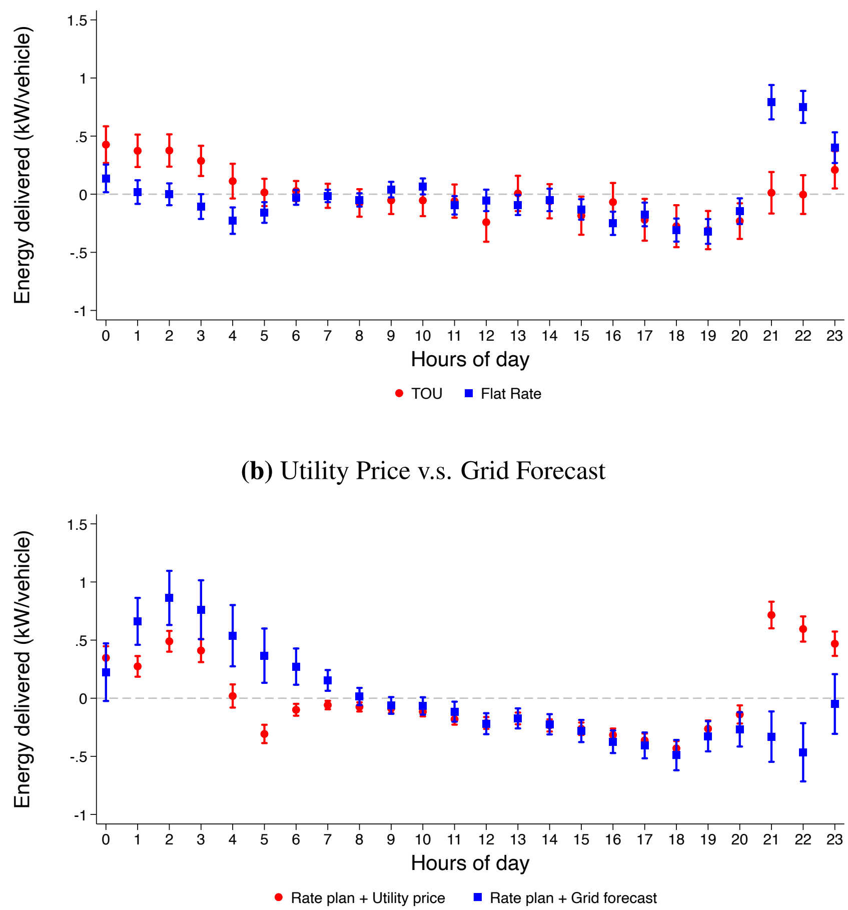
and those on flat rate schedules, highlighting the interaction between rate schedules and managed charging. Second, we examine the heterogeneous effects across charging events under different types of signals. We focus on the two modal signal types: utility price signals, which aims to reducing utilities' 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 6. For vehicles under either rate schedule, we observe a similar reduction 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 0:00. 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 6. 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 6: Effect Heterogeneity of Managed EV Charging on the Load Shape

(a) TOU v.s. Flat Rate



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.

5.3 Where to Charge

Additional to the intended impacts on the load shape, we document an unintended consequence on where to charge the EV. We follow the same empirical strategy as before and examine the effects of the adoption of the managed charging program on the probability of charging at home. The results are shown in Appendix Figure A9. The likelihood of charging at home increases by around 25 percent on the first day since the managed charging adoption, which is mechanical since the managed charging can only be accomplished at home. However, the effect stays stable at about

10 percent afterwards. This is not because of the multi-segment charging patterns if managed as the effect is robust if we restrict the sample to the vehicles that have only one charging events on a day. Therefore, the managed charging adoption also brings the charging load back home, since it becomes relative cheaper to charge at home where the charge events can be managed.

6 Social Value of Managed EV Charging

6.1 Conceptual Framework and Estimation

We evaluate the social values of managed charging based on the estimated effects of managed charging on hourly load. We first define the social values of EV charging, and then measure the changes in the social values if the charging is managed.

For a representative driver i who charges a vehicle on date t, we define the social values of EV charging as follows.

$$V_{it} = \sum_h q_{it}^h \times (v_{it+1} - c_{it}^h - s_{it}^h - e_{it}^h) = \sum_h q_{it}^h \times \{\underbrace{(v_{it+1} - r_{it}^h)}_{\text{driver surplus}} + \underbrace{(r_{it}^h - c_{it}^h)}_{\text{utility profit margin}} + \underbrace{(-e_{it}^h)}_{\text{externality}}\}$$

We use q_{it}^h to represent the load during the hour h. v_{it+1} represents the value of charging to each driver on the next day, which can be harvested after the end of the entire charging event. Since the value of charging doesn't depend on when the energy is delivered, v_{it+1} is not indexed by the hour h. Moreover, r_{it}^h denotes hourly retail electricity price, and $v_{it+1} - r_{it}^h$ is the average surplus to the driver per unit of energy delivered. We use c_{it}^h to represent the hourly wholesale electricity price. $r_{it}^h - c_{it}^h$ measures the unit profit of electricity supply by the utility. e_{it}^h represents the emission externality measured by the hourly marginal rate of emission of CO_2 and local pollutants. Therefore, the total social surplus from EV charging is the sum of the driver surplus, utility profit, and environmental externality.

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 the hourly load under managed charging and under unmanaged charging, respectively. Since managed charging shifts the charging timing but not the total energy delivered, $\sum_h q_{it}^h(1) = \sum_h q_{it}^h(0)$. Consequently, the social value of managed charging can be measured by the change in the social value of EV charging

$$V_{it}(1) - V_{it}(0) \approx \underbrace{-\sum_h [q_{it}^h(1) - q_{it}^h(0)] \times r_{it}^h}_{\text{drivers' charging expenditure}} + \underbrace{\sum_h [q_{it}^h(1) - q_{it}^h(0)] \times (r_{it}^h - c_{it}^h)}_{\text{utilities's profit from load shift}}$$
$$\underbrace{-\sum_h [q_{it}^h(1) - q_{it}^h(0)] \times e_{it}^h}_{\text{environmental externality}}.$$

The social value of managed charging can be decomposed into four parts. First, managed charging shifts hourly load and changes the total expenditure on EV charging for drivers. Second, managed charging shifts hourly load and changes the total profit of electricity supply for utilities. Third, by shifting hourly load, managed charging induces changes in the wholesale electricity prices and affects the utility profit. Fourth, managed charging alters the environmental externality of the load.

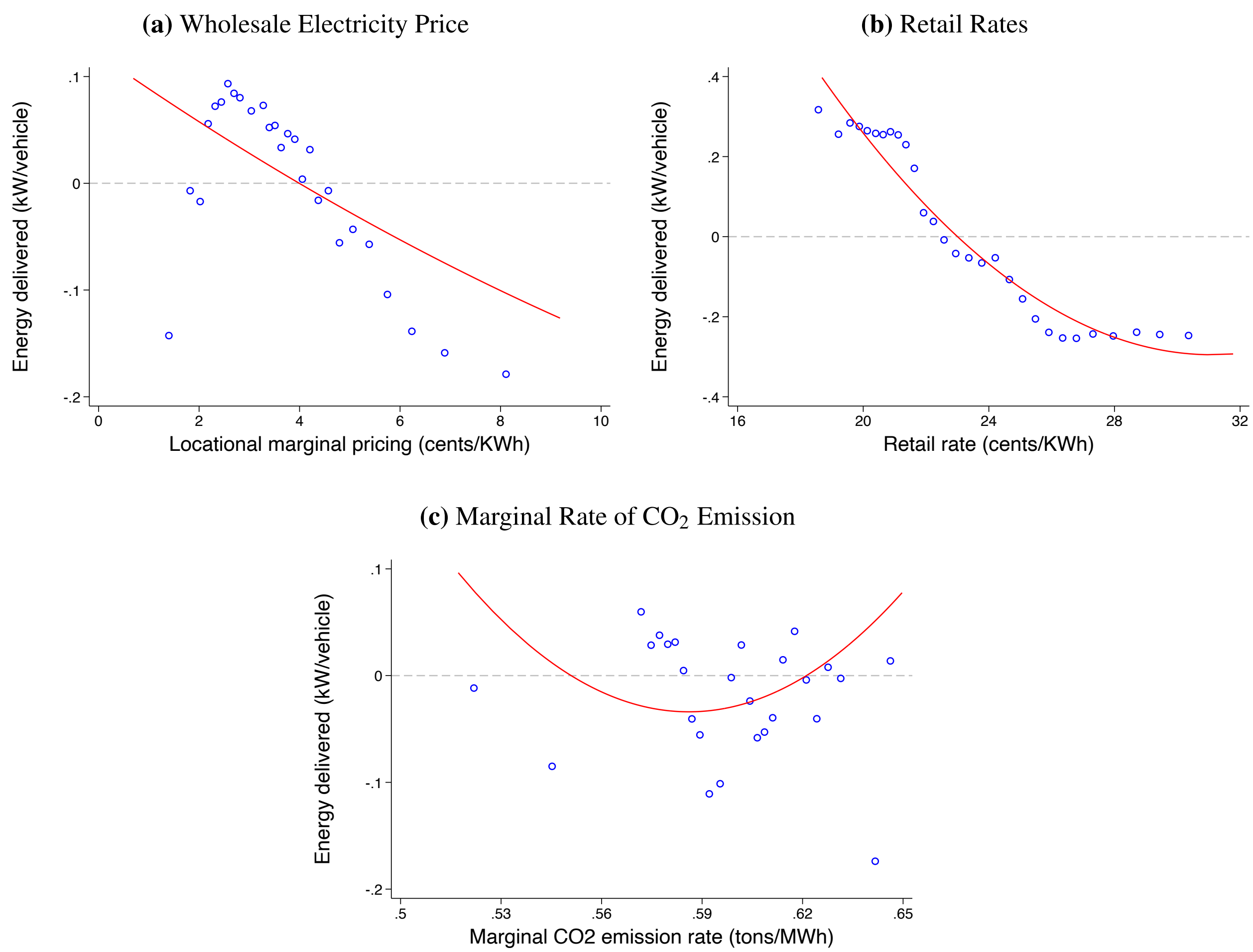
6.2 Quantification of Social Values

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 the marginal rate of emission 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 7. 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 clear relationship between the load changes and environmental externality.

Figure 7: 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 dollars per day of charging and utilities could pay 1 dollar on average for the electricity generation. The managed EV charging saves the cost for EV drivers by about 60 dollars per year per vehicle and 2.7 percent of the cost if unmanaged, while the electricity generation cost of utilities would fall by about 12 dollars per year per vehicle and 3.1 percent from the profit if unmanaged. The impacts on the environmental externality is marginal, only a decrease of 1 dollar per year per vehicle. On net, the social value per vehicle increases by around 15 dollars per year, which is a 7.7 percent gain from the level if unmanaged. Consequently, the managed EV charging shifts the utility profit to the cost saving of consumers, and on average improves the social value of EV charging.

Table 1: Social Value of the 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 welfare calculation of the managed charging as well as the decompositions.

However, we notice 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 and Discussion

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 (Not for Publication)

Hunt Allcott Luming Chen

Table of Contents

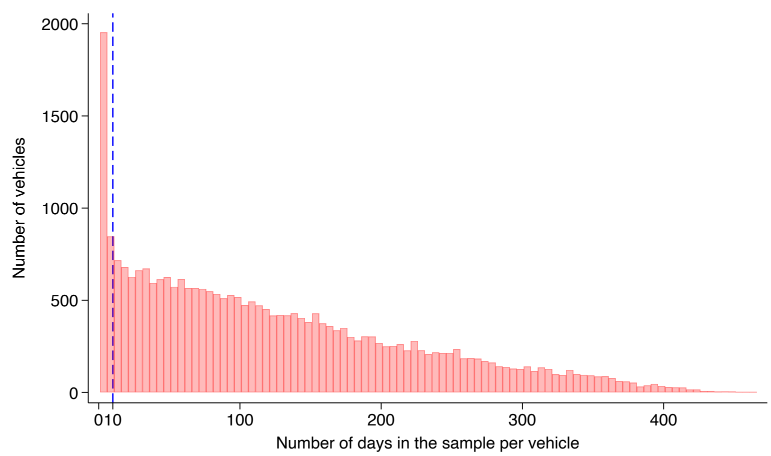
A Data Cleaning

A.1 Days in the Sample

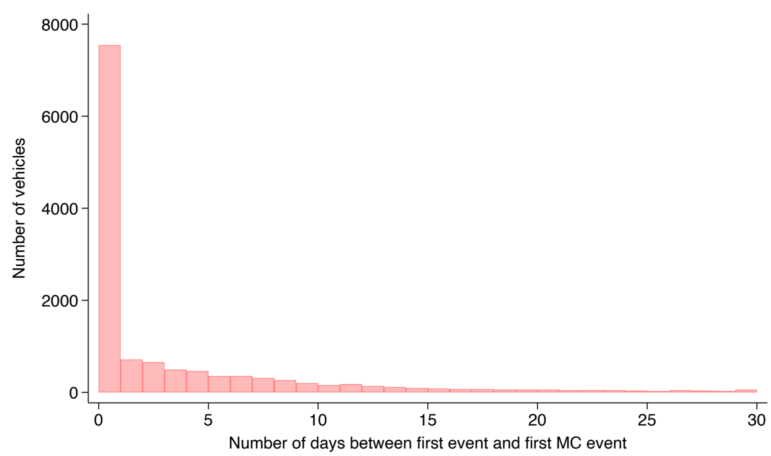
We first plot the number of days in the sample for each vehicle in Panel (a) of Figure A1. Vehicles on average have 123 days in the sample. However, 2.5 percent of the vehicles only have one day of observations in the sample, and 9.8 percent of the vehicles have fewer than 10 days of observations in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

$$q^h_{ijt}(0) = \delta^h_i \kappa_t + \gamma^h_t + \beta^h x_j + \varepsilon^h_{ijt}. \tag{3}$$

$q^h_{ijt}(0)$ 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 (3) 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 (3) 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.

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

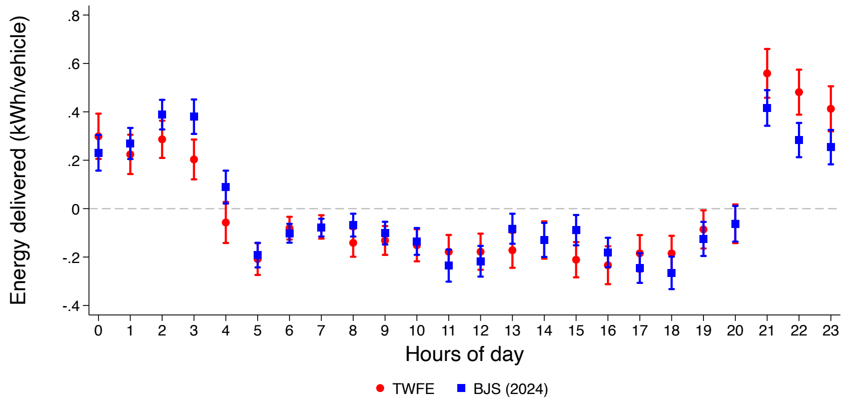
We group vehicles and days according to the number of dates since the adoption of the managed charging program, denoted as d. We examine the coefficient of τ_d between 12 days before the managed charging adoption and 30 days after that.

The average treatment effect τ is defined as below.

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

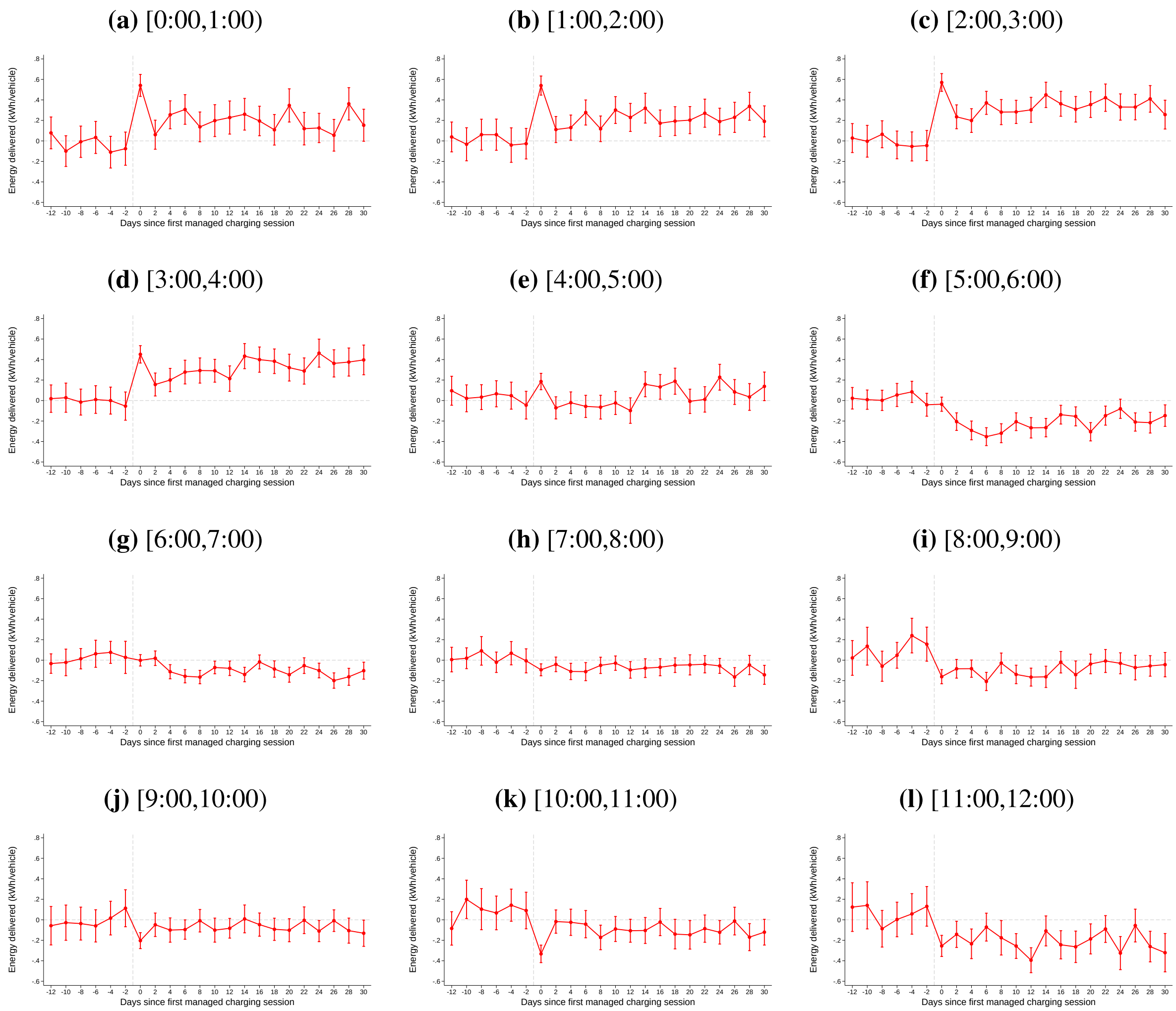
The full event study results following Borusyak et al. (2024) are shown in Figures A3 and A4, which are quantitatively similar to the event study results using TWFE. We plot the estimated average effects on the hourly load using the TWFE model and the imputation-based estimator in Figure A2. The two 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.

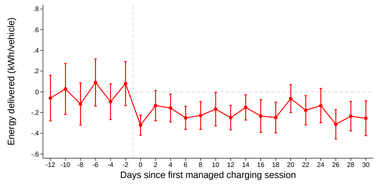
Figure A3: The Effects of Managed Charging on Hourly Load (AM, Imputation-based)



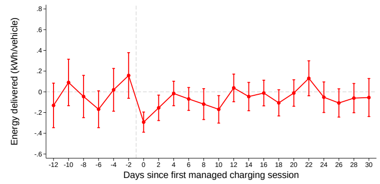
Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 am and 12:00 pm. The estimation follows Borusyak et al. (2024) and is discussed in detail in Appendix Section B. 95% confidence intervals are plotted with standard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

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

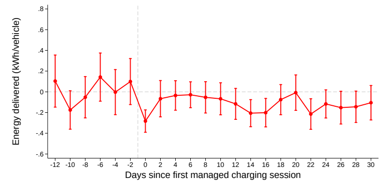
(a) [12:00,13:00)



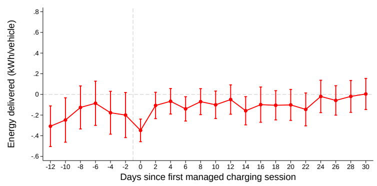
(b) [13:00,14:00)



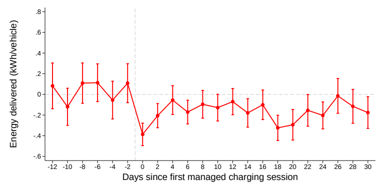
(c) [14:00,15:00)



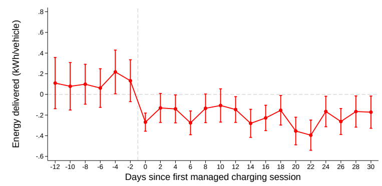
(d) [15:00,16:00)



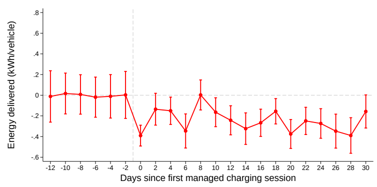
(e) [16:00,17:00)



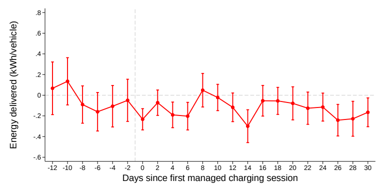
(f) [17:00,18:00)



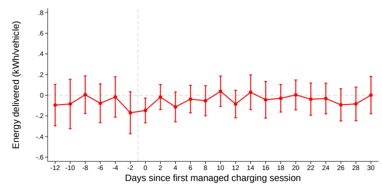
(g) [18:00,19:00)



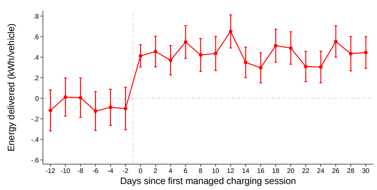
(h) [19:00,20:00)



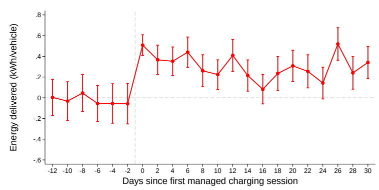
(i) [20:00,21:00)



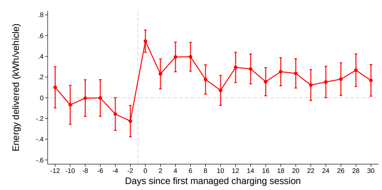
(j) [21:00,22:00)



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



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

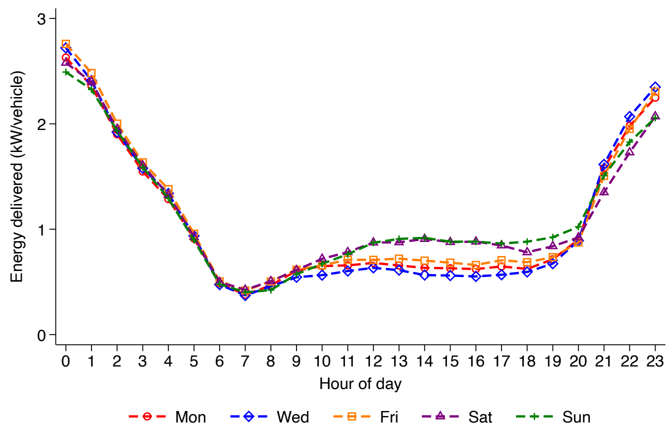


Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 pm and 0:00 am (on the next day). The estimation follows Borusyak et al. (2024) and is discussed in detail in Appendix Section B. 95% confidence intervals are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

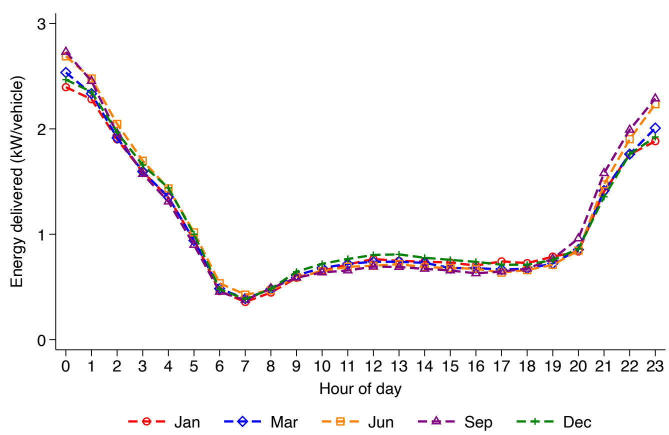
C Additional Figures and Tables

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

(a) Days of the Week



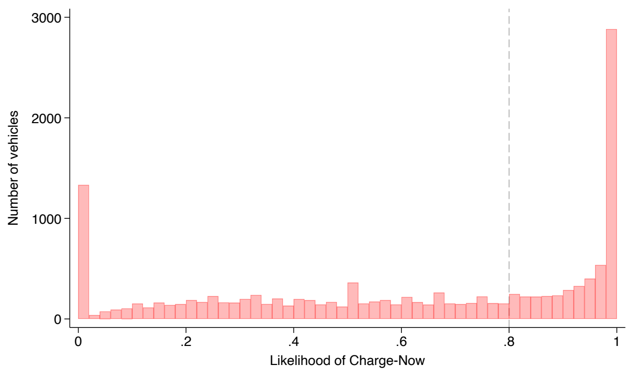
(b) Months



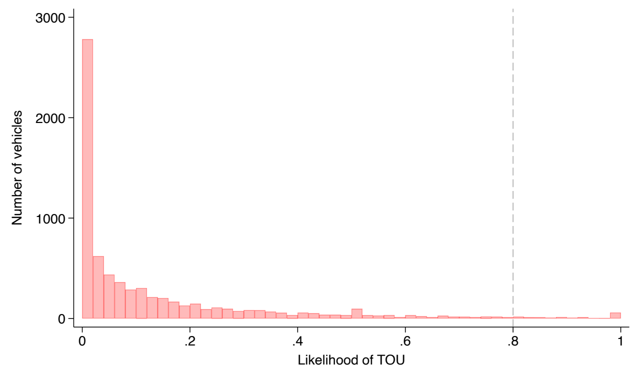
Notes: This figure plots the average load shape across hours of a day for vehicles that are never under the managed charging during the sample window. Panel (a) plots the average load shape by day of a week. Panel (b) plots the average load shape by month.

Figure A6: Load Shape for Never-Managed Vehicles

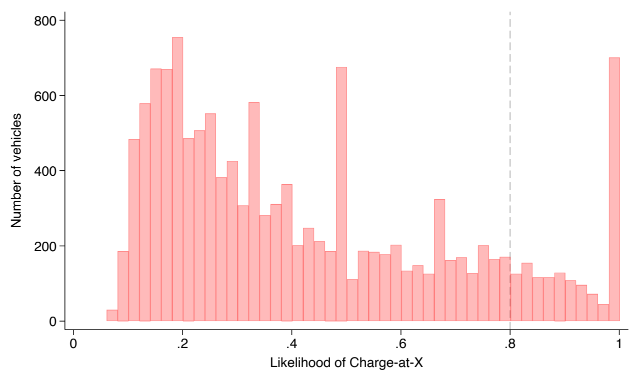
(a) Charge Now



(b) TOU

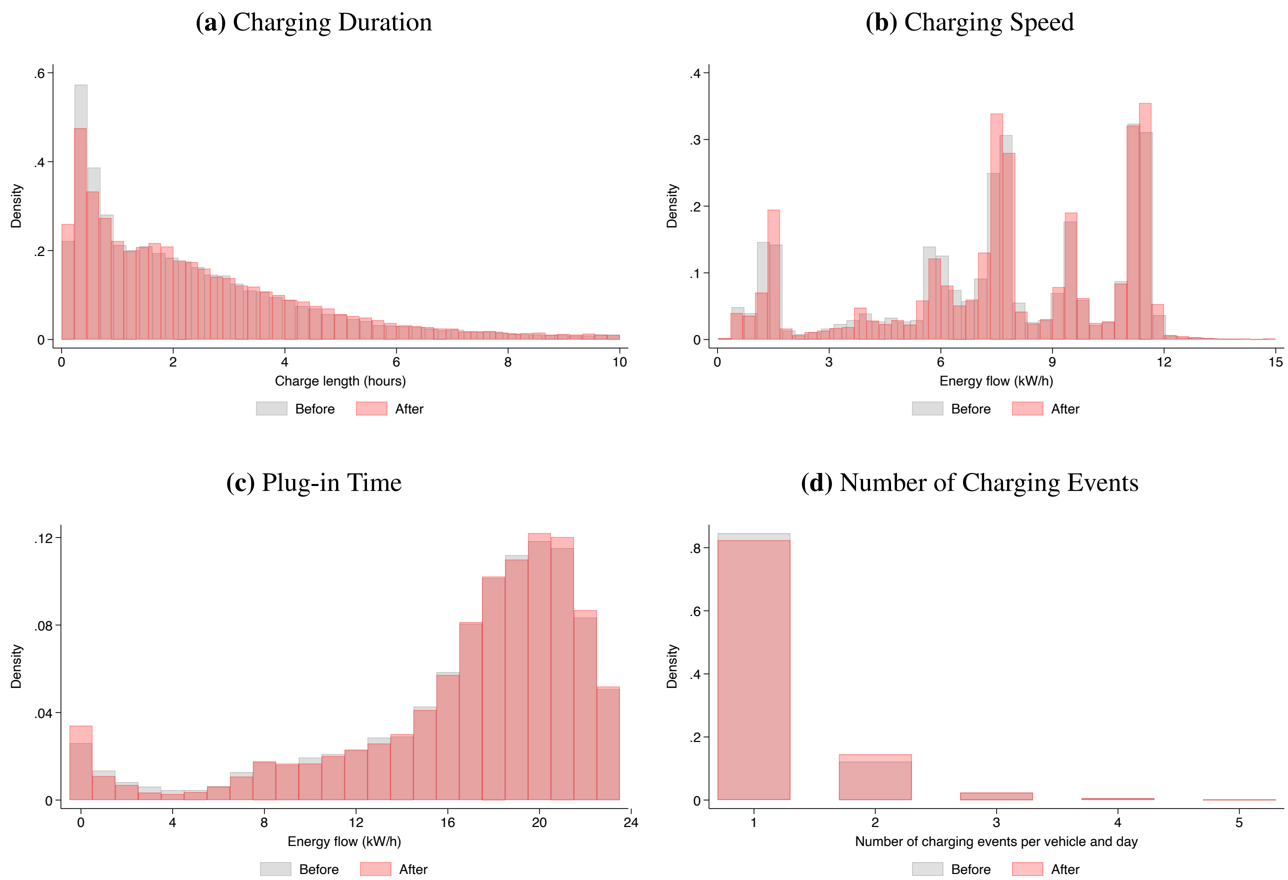


(c) Charge at X



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.

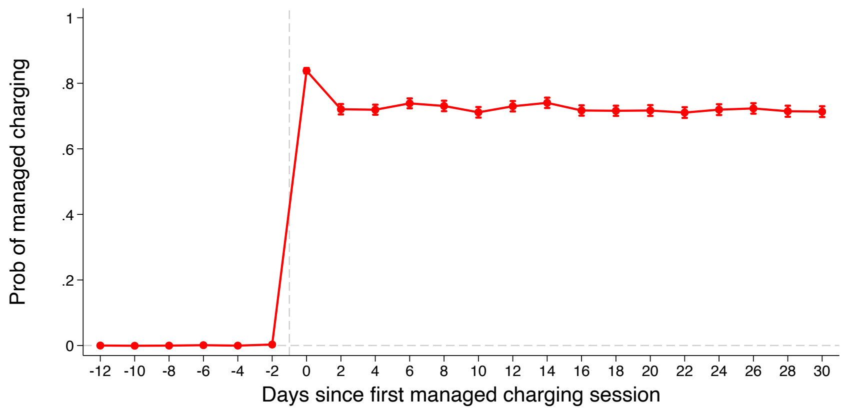
Figure A7: Before-after Comparison of Other Charging Characteristics



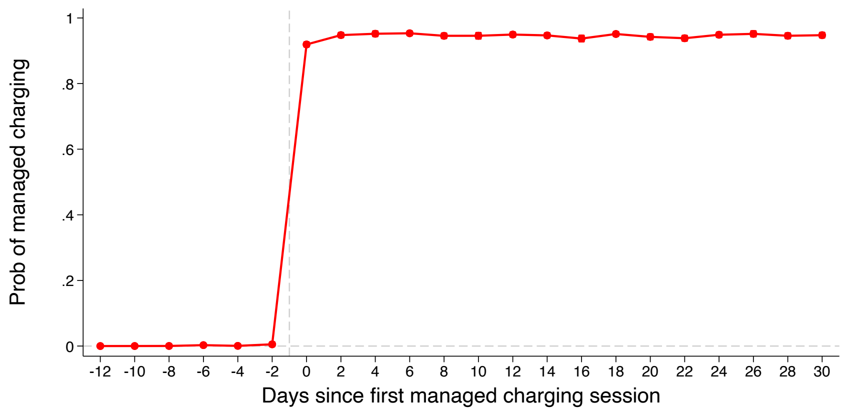
Notes: This figure compares three characteristics of charging events before and after the vehicles adopt the managed charging program. Panel (a) plots the distribution of the durations of the charging events, Panel (b) plots the distribution of the durations of the charging speed, Panel (c) plots the 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

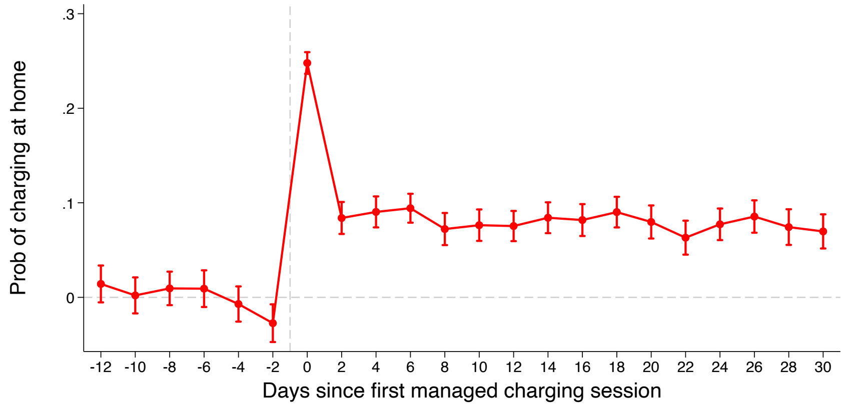


(b) At-home Charge Events Being Managed



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.

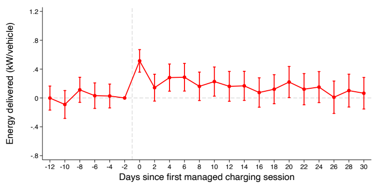
Figure A9: Probability of Charging at Home



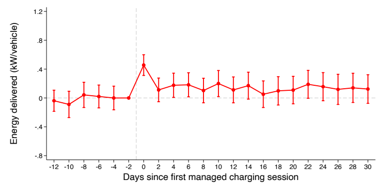
Notes: This figure plots the effects of the managed charging adoption on the likelihood of the charging events being at home. The estimation follows Borusyak et al. (2024) and is discussed in detail in Section (4). 95% confidence intervals are plotted with standard errors clustered at the vehicle level.

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

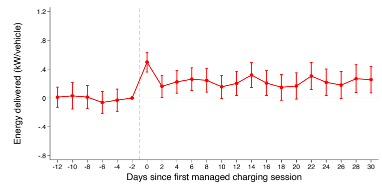
(a) [0:00,1:00)



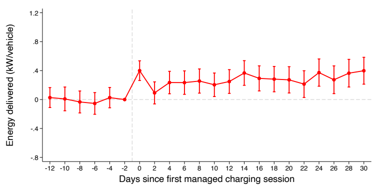
(b) [1:00,2:00)



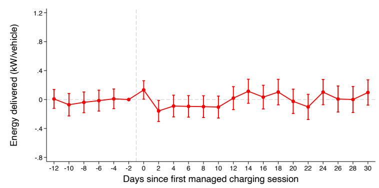
(c) [2:00,3:00)



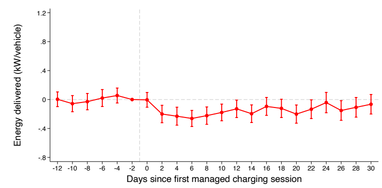
(d) [3:00,4:00)



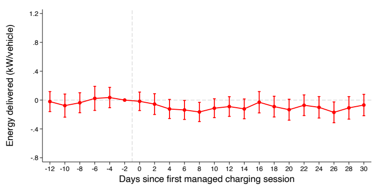
(e) [4:00,5:00)



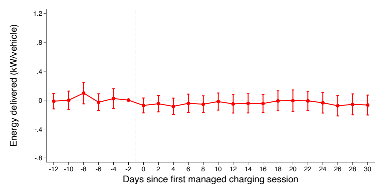
(f) [5:00,6:00)



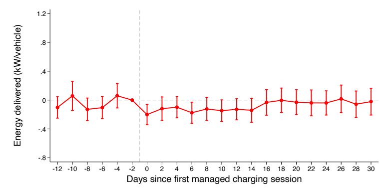
(g) [6:00,7:00)



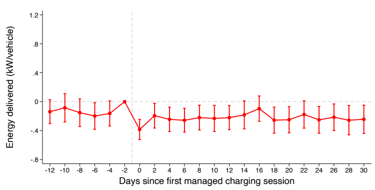
(h) [7:00,8:00)



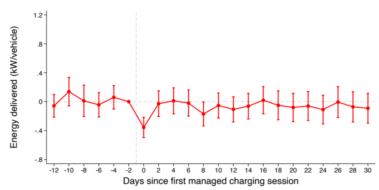
(i) [8:00,9:00)



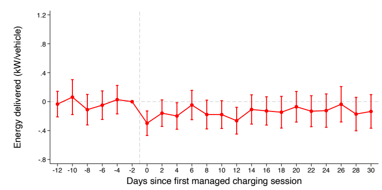
(j) [9:00,10:00)



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



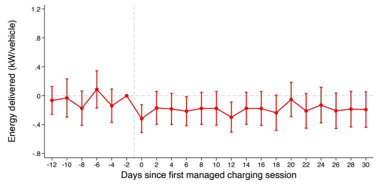
(l) [11:00,12:00)



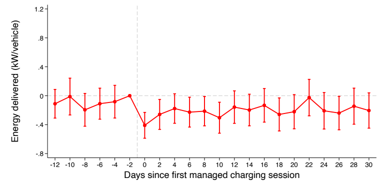
Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 am and 12:00 pm. The estimation uses the TWFE model and follows equation 1. 95% confidence intervals are plotted with standard errors clustered at the vehicle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

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

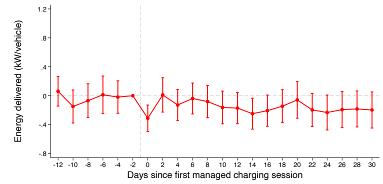
(a) [12:00,13:00)



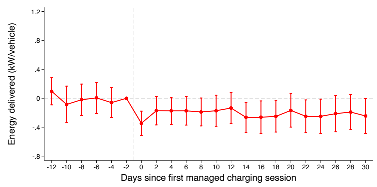
(b) [13:00,14:00)



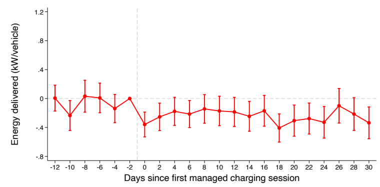
(c) [14:00,15:00)



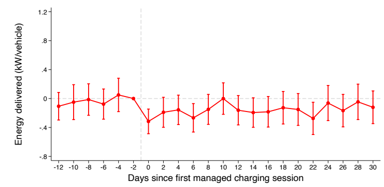
(d) [15:00,16:00)



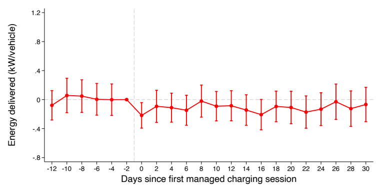
(e) [16:00,17:00)



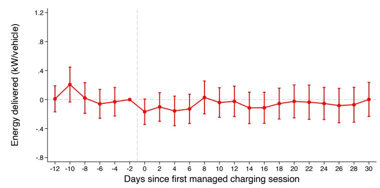
(f) [17:00,18:00)



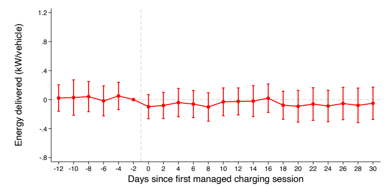
(g) [18:00,19:00)



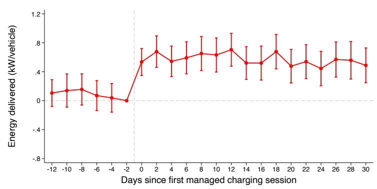
(h) [19:00,20:00)



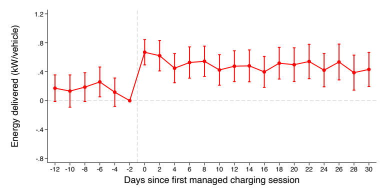
(i) [20:00,21:00)



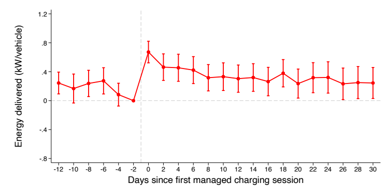
(j) [21:00,22:00)



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



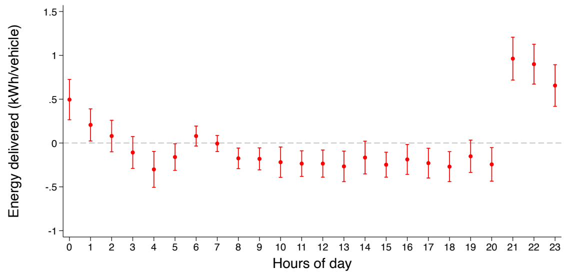
(l) [23:00,0:00)



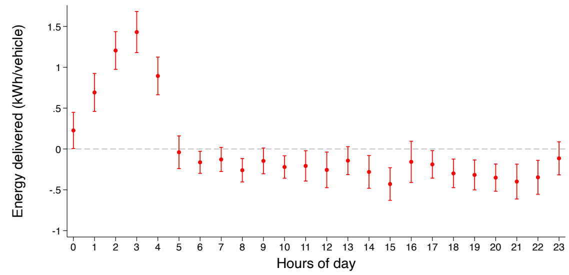
Notes: This figure plots the effects of managed charging on the average hourly load. We present the event studies for every hour between 12:00 pm and 0:00 am. The estimation uses the TWFE model and follows equation 1. 95% confidence intervals are plotted with standard errors clustered at the vehicle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

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

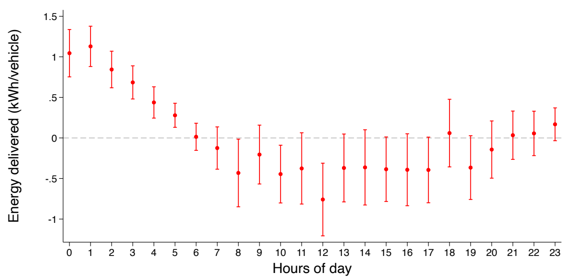
(a) Utility no. 2



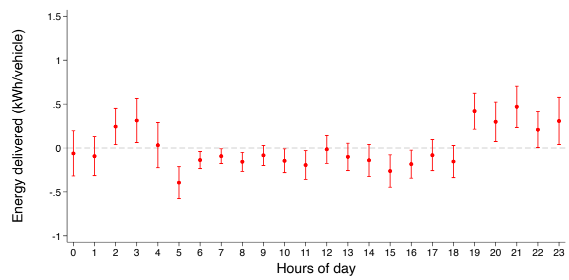
(b) Utility no. 5



(c) Utility no. 8



(d) Utility no. 13



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.