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The impact of co-adopting electric vehicles, solar photovoltaics, and battery storage on electricity consumption patterns: Empirical evidence from Arizona

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ABSTRACT

Electric vehicles, residential rooftop solar photovoltaics, and home battery storage contribute to a reliable, resilient, affordable, and clean power grid. To accelerate decarbonization, large-scale deployment of these distributed technologies will be indispensable but cause significant impacts on the power grid in the future. This study provides the first empirical evidence of the impact of co-adopting the three technologies on electricity consumption patterns based on smart meter data of three representative adopters from Arizona. The estimated overall impact of the coadoption on average hourly net load is -0.68 kWh. An intraday consumption transfer is identified. Leveraging the three technologies, consumers reduced electricity consumption from the grid during the day and early evening, increased consumption in the late evening, and exported excess electricity to the grid during the day. We also estimate the decomposed impacts of each adopted technology.

1. Introduction

Electric vehicles play a key role in electrification and have gained great attention over the last decade. With continued strong growth, the total number of electric vehicles on the road worldwide was 16.5 million by the end of 2021, three times the number in 2018 (IEA, 2022). Replacing gasoline vehicles with electric vehicles helps control emissions from burning gasoline in the transportation sector, which is a major contributor to greenhouse gas emissions from all countries and is currently the largest emitting sector in the United States (US EPA, 2022). However, charging electric vehicles with the current power grid still causes environmental damage—both from local air pollution and from Greenhouse Gases (GHGs)—because some power plants use dirty fuels, such as coal, for generation (Holland et al., 2016). Full decarbonization of the transport sector requires that it not only becomes all-electric, but that electricity is generated from renewable energy or other low-carbon sources (Qiu et al., 2022b).

Solar photovoltaics (PV) are a renewable and clean source of energy. Residential solar PV has been adopted by an increasing number of households worldwide (IEA, 2020) and can be used for generating electricity at home and saving energy bills. It can provide clean electricity for electric vehicles, which further reduces the environmental damage of traffic (Muratori, 2018). However, solar PV is only able to generate electricity during the day with sunlight.

Home battery storage is another new green technology, which stores the electricity delivered from the grid or generated by residential solar PV. It has been discussed widely in recent literature (Ratnam et al., 2015; Ranaweera and Midtgård, 2016; Jargstorf et al., 2015). The home battery can store the excess solar electricity during the day and then discharge the electricity at night when the solar power generation is not available. The battery can also be charged at off-peak hours (with lower electricity prices) and discharged at peak hours (with higher prices) to save energy bills. This intraday transfer of electricity usage helps reduce grid load variability contributing to a more reliable, resilient, and affordable power grid (Qiu et al., 2022a; Freitas Gomes et al., 2020; Nyholm et al., 2016).

To help achieve deep decarbonization, there is an urgent need to promote these three technologies on a large scale. Many governments

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Table 1
Summary of three consumers who installed the three technologies.

	Treated Consumer #1	Treated Consumer #2	Treated Consumer #3
Solar PV adoption date	2–10–2017	6–22–2018	9–6–2018
Battery adoption date	9–18–2018	6–22–2018	9–6–2018
EV adoption date	9–1–2017	11–1–2018	4–1–2019
Observed period	5–1–2013 to 4–30–2019		
Average hourly electricity consumption (kWh) from the grid	2.12	1.42	1.12
Standard deviation of hourly electricity consumption (kWh) from the grid	2.07	1.45	1.24
Electricity rate plan	Plan 23 (before 2–10–2017) Plan 27 (since 2–10–2017)	Plan 23 (before 6–22–2018) Plan 27 (since 6–22–2018)	Plan 21 (before 9–6–2018) Plan 27 (since 9–6–2018)

Note: Rate plan 23 is SRP Basic Price Plan, which has a flat rate for all hours; plan 21 is SRP EZ-3 Super peak Time-of-Use Price Plan, and plan 27 is Customer Generation Price Plan. In plan 21, on-peak hours are 3- 6 p.m. Monday to Friday and the rest are off-peak hours. In plan 27, on-peak hours are 2- 8 p.m. in summer and 5–9 a.m. & 5–9 p.m. in winter, Monday to Friday, and the rest are off-peak hours. In both plans 21 and 27, the rate is higher during on-peak hours. In all three plans, rates are seasonally adjusted. Rates are higher in summer than in winter. Detailed descriptions of the rate plans can be found on SRP's website: https://www.srpnet.com/menu/electricres/priceplans.aspx and Appendix A.

and utilities have introduced a variety of incentives to encourage consumers to adopt these technologies. Although the current penetration rate of co-adopting the three technologies is low, large-scale deployment of these distributed energy technologies with uncertain charge and discharge patterns in the future will have a significant impact on the power grid and bring challenges for future power grid management (Tran et al., 2019). Consumers could have different motivations to adopt these three technologies, such as the maximization of self-sufficiency, the minimization of electricity bills, or the maximal use of renewable electricity. The diverse motivations imply different strategies for using these technologies and different changes in electric consumption patterns. Also, the impact of co-adopting the three technologies could be different from a simple combination of adopting each technology individually (Qiu et al., 2022a). Thus, a full understanding of the behavior changes and the overall impact on the grid after co-adopting these technologies is urgently needed.

This paper explores the impacts of these three technologies with evidence from Arizona. Arizona is one of the states that is deeply involved in the clean energy transition in the U.S. It has the seventh-highest number of registered electric vehicles in the U.S. at around 40,740 as of 2022 (Department of Energy US, 2022), and it has the fifth-highest number of installed solar panels at around 5984 MW as of 2022 (Solar Energy Industries Association, 2022). Unlike the above two technologies, still very few consumers installed home battery storage in Arizona. In this study, we provide the first empirical evidence of the overall and decomposed impacts of co-adopting these three residential green technologies (electric vehicles, solar PV, and battery storage) on electricity consumption patterns and their impact on the power grid. Based on the high-frequency smart meter data of three representative adopters in Phoenix, Arizona (who installed all the three technologies within a short period and share a similar level of electricity consumption with normal users) and using the difference-in-differences method in conjunction with matching, we estimate the net impact of the coadoption on electricity consumption patterns compared to consumers who did not adopt any of the three technologies. In addition, leveraging a machine learning algorithm, we explore potential behavior changes by estimating the short-run changes in electricity consumption patterns after installing each technology for each individual user, respectively.

We provide two major contributions to the literature. First, this paper builds upon the empirical studies investigating the impact of adopting clean energy technologies, such as solar PV, electric vehicles, and heat pumps, on electricity consumption patterns (Qiu et al., 2019, 2022a, 2022b; Liang et al., 2022; McKenna et al., 2018). These studies only estimate the impact of a single-technology adoption or a coadoption of two technologies (such as solar PV and battery storage) (Qiu et al., 2022a). Currently, few users install electric vehicles, solar PV, and battery storage at the same time. For instance, only 8 users installed all the three technologies in our sample of 13,279 users in Arizona. We provide a pilot empirical study investigating the impact of co-adopting these three residential clean technologies, which has leading implications for the future large-scale deployment. Second, previous engineering studies used simulation-based approaches to explore the impacts of single-technology adoption (Muratori, 2018; Harris and Webber, 2014) and multi-technology integration (Ding et al., 2010; Li et al., 2018) on the power grid. The simulation-based approaches have shortcomings relying on the pre-determined assumptions about consumer responses and technology-usage patterns (Muratori, 2018): (1) Assuming that technologies are used according to established patterns (e.g., charging electric vehicles only during the off-peak hours); (2) Assuming that all the consumers share a similar behavior pattern. Recent empirical studies (Qiu et al., 2022a, 2022b) have shown that the heterogeneous changes in consumption patterns of clean residential technologies differ from simulation-based predictions. Our study based on actual smart meter data does not rely on pre-determined assumptions and provides more accurate estimates.

This paper is structured as follows. Section 2 describes methodological approaches and data, and Section 3 shows estimated results. Section 4 concludes the paper with discussion and policy implications.

2. Methods

2.1. Data

We obtained the high-frequency smart meter data from the Salt River Project, an electrical utility company serving the Phoenix metropolitan area. Our dataset includes electricity flows (hourly kWh delivered from and to the power grid) of 13,279 residential users from 1st May 2013 to 30th April 2019. The dataset also records the solar PV adoption date, home battery storage adoption date, and date of starting the electrical vehicle in-home charging, electricity rate plan, and ZIP code for each individual user. Among the users of our dataset, 2220 users adopted the electric vehicle and started charging it during the time window of the dataset. Among these electric vehicle users, 8 users adopted residential battery storage and 333 users adopted solar PV in our observed period. 11,059 users did not adopt any of the three technologies. To sum up, 8 users installed all the three technologies in our dataset. Only 3 users adopted the three technologies within a short term (e.g., within one year). To support the analysis, we obtained the hourly temperature in the city of Phoenix from the website of the National Oceanic and Atmospheric Administration (2022).

2.2. Difference-in-differences in conjunction with matching

To estimate the overall impact of adopting electric vehicles, solar photovoltaics, and battery storage on electricity consumption patterns, we focus on three outcomes, namely hourly kWh delivered from the grid to consumers, hourly kWh sent back to the grid, and net load (which is the amount of hourly kWh delivered from the grid minus the amount sent to the grid). To address the selection bias and omitted variable bias, we utilize the difference-in-differences approach in conjunction with

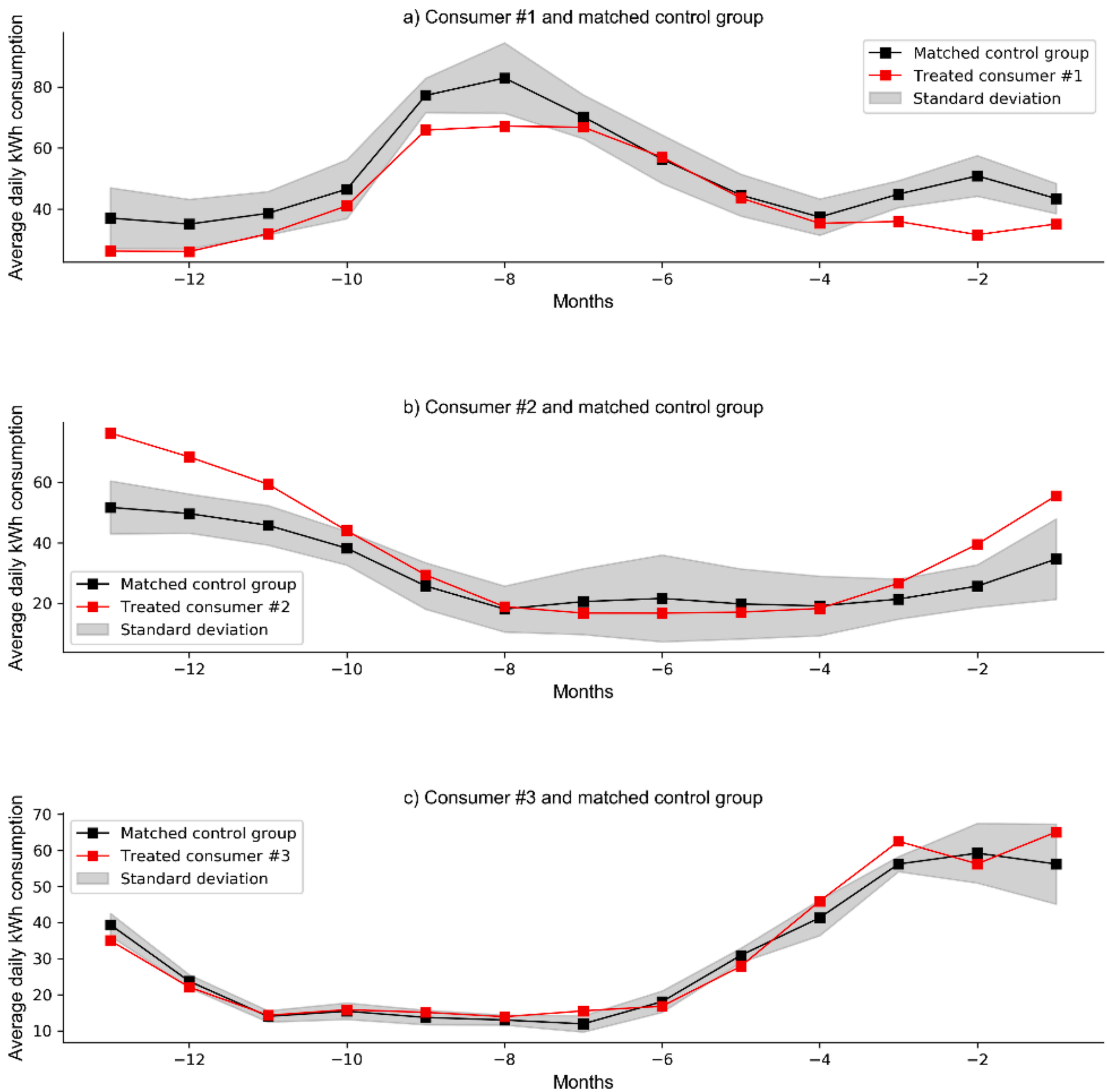

Fig. 1. Trends of monthly electricity consumption one year prior to the adoption of three technologies between the treated users and their corresponding control groups.

matching to estimate the impacts (Angrist and Pischke, 2008). Intuitively, we compare changes in electricity flows in households before and after adopting the three technologies with those in households in the control group, which helps control both time-invariant and time-variant confounding factors. We use households who did not install these technologies but shared similar electricity demands as the control group. We aim to estimate the average treatment effect on treated (ATT) (Angrist and Pischke, 2008), and the treatment of interest in this study is adopting three technologies successively within a short term. The dates of adopting different technologies are different, so the treatment did not happen in a single day. To relieve the concern on the confounding factors of time-variant behavior changes along with the adoption process of the three technologies, this study focuses on the sample of users who installed the three technologies within a relatively short term (e.g., within 1 year). In our dataset, 3 consumers installed the three technologies within a short term, who serve as the treated group in the difference-in-differences study design. See descriptive information of the three users in Table 1. The electricity consumption amounts of the three treated consumers are similar to normal consumers in the Phoenix metropolitan area.

Then, we utilize the methods of Exact Matching and Coarsened Exact Matching (CEM) (Iacus et al., 2012) to find comparable users, who did not install any of the three technologies, as a control group. We first conduct the exact matching on the ZIP code and electricity rate plan in the pre-treatment period. After the exact matching, each treated user and their control users are located in the same ZIP code area and share the same electricity rate plan in the pre-treatment period.[1] We remove the control users who changed their rate plan in the time window of analysis from the sample, which means that the rate plan of control users is fixed in our sample. Second, we conduct CEM on two new generated covariates, namely average daily electricity consumption (delivered from the grid) and the standard deviation of daily electricity consumption, to find comparable treated and control users sharing similar electricity consumption patterns. The CEM method coarsens the covariates into a number of bins and then finds exact matches based on the coarsened bins. In our analysis, we use a Stata-default CEM algorithm to conduct the CEM for each treated user, respectively. 104, 61, and 43 bins are automatically generated by Stata for matching. At last, 13, 5, and 3 comparable control users are matched to each treated user.

Fig. 1 plots the trends of monthly electricity consumption one year prior to the adoption of the three technologies between treated users and their corresponding control users. Points in the figure are the average daily electricity consumption within each month. Shaded areas in the figure show the standard deviation of the consumption of control groups each month. Treated and control users share similar monthly trends of electricity consumption in the pre-treatment period, which supports the key assumption of our difference-in-differences research design, namely the parallel trend assumption (Roth, 2019). We also formally test the parallel trend assumption by running a statistic regression (See the statistic test procedures and results in Appendix B).

Then, we apply a two-way fixed effects model to obtain the difference-in-differences estimator by comparing the changes in outcomes of interest (e.g., kWh delivered from the grid and net load) of treated users before and after adopting the three green technologies with those of control users in the same period. The following regression is applied:

$$Y_{it} = \sum_{j=1}^{24} \beta_j H_j \cdot D_{it} + \sum_{p=1}^{5} \alpha_p f_p(TEMP_t) + \sum \pi_k + \mu_t + \rho_t + \sigma_t + \tau_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the outcome variable for consumer i at time t. We examined two outcomes in this difference-in-differences model, namely hourly electricity consumption (kWh) delivered from the grid and hourly net load (kWh), respectively; H_j are 24 hour-of-day indicators; D_{it} is the treatment variable, which takes value one for treated users after installing the three technologies and takes value zero before the adoption of the first technology; We use a spline function f_p to represent the heterogeneous responses of electricity consumption to temperature (Anderson, 2014; Shen et al., 2021) and four knots are identified to divide the temperature into five bins; $TEMP_t$ is the hourly temperature in the city of Phoenix; π_k are a series of dummy variables indicating national holidays in the U.S.; μ_t is the season-by-hour-of-day fixed effects, which help control for common intraday electricity consumption patterns by the three different seasons (summer, summer peak, and winter) defined by the SRP utility.[2] ρ_t, σ_t, τ_t are year fixed effects, month-of-year fixed effects, and day-of-week fixed effects. ε_{it} is the error term. Standard errors are clustered at the individual consumer level. Observations between dates of installations of different technologies are removed from our sample so that we can estimate the net impact of adopting all three technologies relative to consumers who did not install any of the technologies. The pre-treatment period in the sample of our analysis is one year prior to the adoption date of the first technology and the post-treatment period is from the adoption date of the last technology to April 30th, 2019. Interpreting the coefficient of β_j in our model should be cautious, since all the three treated users changed their electricity rate plan to "E27 customer generation price plan" after they installed the solar PV and stayed with the E27 plan until the end of our analysis time window. Thus, our estimated impact is caused by a combination of co-adopting technologies and changing rate plans. Detailed interpretation of results is discussed in Section 3.

We also examined the impact of the coadoption on hourly electricity (kWh) sent back to the grid. Since there is no electricity sent to the grid without the adoption of these three technologies, the treatment effect is simply the observed amount of electricity sent back to the grid after the coadoption. We report the average and standard deviation of hourly kWh sent to the grid in Section 3.1.

2.3. Counterfactuals prediction based on a machine learning algorithm

To understand and decompose the overall impact of co-adopting the three technologies, we explore the short-run changes in electricity consumption patterns (hourly kWh delivered from and to the grid) after adopting each technology for each treated consumer, respectively.

It is relatively easier to find comparable control users for estimating the overall impact of three technologies since the control users are among the most common group who did not adopt any of the three technologies. It is harder to find comparable control consumers for every stage of technology adoption and for every treated consumer if we apply the same difference-in-differences study design to estimate the impact of each technology. For example, if we aim to estimate the impact of adopting an electrical vehicle on consumer #1′s electricity consumption pattern, we need to find comparable control users who have installed solar PV and share the same electricity rate plan and similar electricity consumption pattern. Thus, in this section of analysis, we apply a machine learning algorithm, namely the Random Forest algorithm (Breiman, 2001; Meinshausen and Ridgeway, 2006), to construct the counterfactuals of electricity flows (kWh delivered from and to the grid) if the treated users had not installed a green technology only based on the long time-series data of treated users prior to adopting the technology. The flexible machine learning model can better fit the complex and non-linear relationship between residential electricity consumption and other factors, such as temperature, season, time of day, and many others (Jarvis et al., 2022; Burlig et al., 2020). Thus, the machine learning model shows more advantages in constructing counterfactuals compared to traditional linear regression models. The machine learning methods have been applied by many studies to generate counterfactuals (Varian, 2014, 2016; Athey et al., 2021; Carvalho et al., 2018) and evaluate the performance of energy efficiency programs (Burlig et al., 2020; Souza, 2020; O'Neill and Weeks, 2018).

For each technology adoption by each user, we use the time-series data of the individual user from one year before the adoption to one month after the adoption for analysis.[3] Training data, the time-series data before the adoption, is used for training the Random Forest algorithm. Testing data, one month after the adoption, is used for predicting the counterfactuals with the trained machine learning model. Since the training data does not include any information about adopting the technology, our approach can estimate the electricity flows under a scenario where the consumer did not install the technology. The difference between actual flows and predicted counterfactuals is the treatment effect of adopting the technology. We only predict the counterfactuals in the short term (within a month) to relieve the influence of time-variant confounding factors. For example, the users may also install other energy-efficient appliances after adopting the technology of our interest and may change their electricity consumption patterns. Focusing on a small time window (such as one month) can reduce the possibility of the above confounding factor.

[1] All the three treated users switched their electrical rate plan to rate plan 27 "Customer Generation Price Plan" after they installed the solar PV.

[2] In SRP rate plan, three seasons are defined. Summer season is defined as May, June, September and October. Summer peak is July and August. Winter is from November to April.

[3] When we estimate the impact of adopting EV on electricity sent back to grid of the three treated consumers, the pre-treatment time-series data of hourly kWh sent to grid are less than one year.

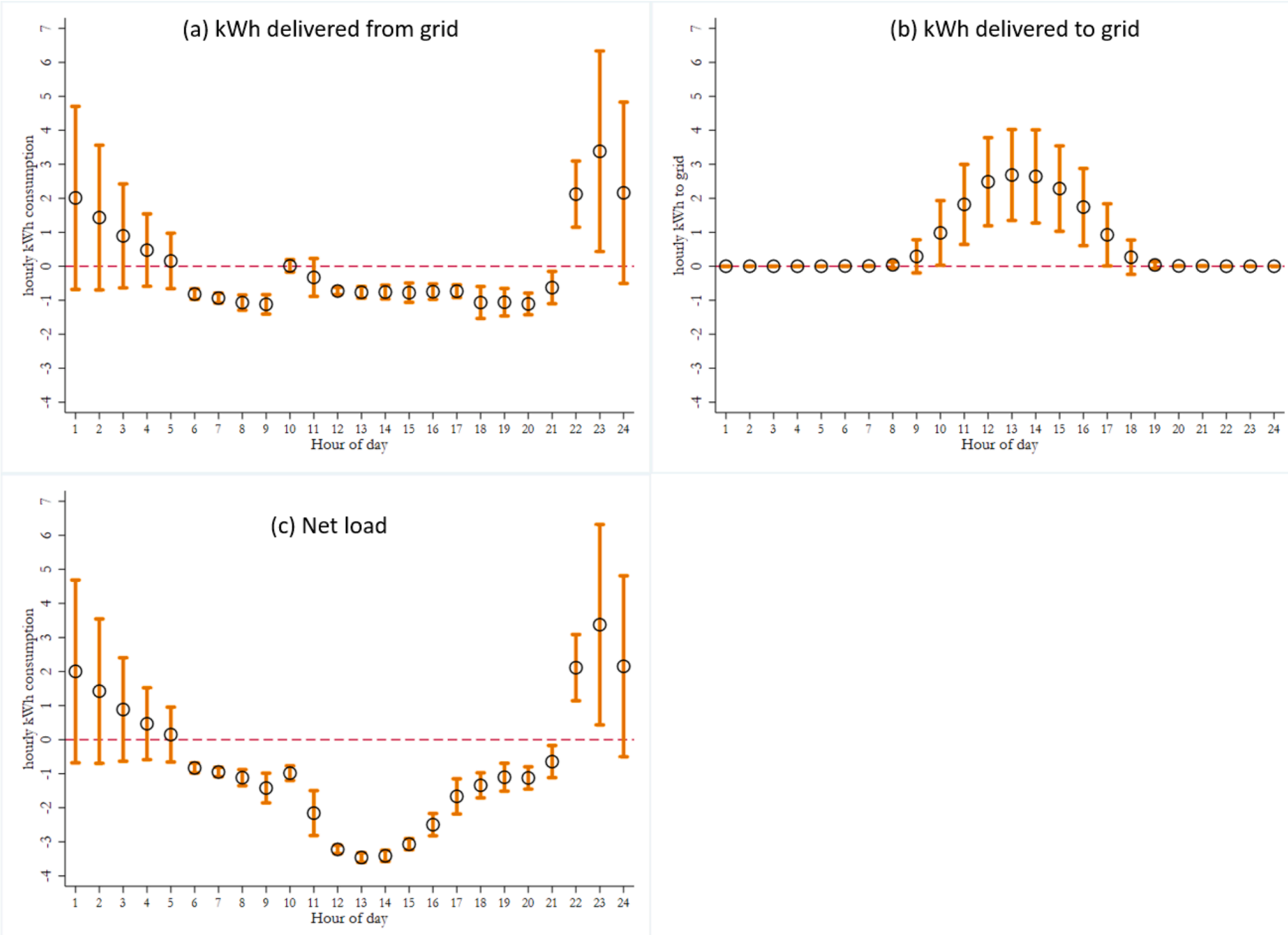

Fig. 2. The overall impact of co-adopting electric vehicles, solar photovoltaics, and battery storage on hourly electricity flows (kWh delivered from the power grid, to the grid, and net load). Note: circles are point estimators, error bars in subplot (a) and (c) are 95% confidence intervals, and error bars in subplot (b) are standard deviation.

The input variables in the Random Forest model include hourly temperature, day-of-month fixed effects, month-of-year fixed effects, year fixed effects, day-of-week fixed effects, hour-of-day fixed effects, national holidays fixed effects, electricity rate plan fixed effects, and three dummies indicating the adoption status of the three technologies. We check the performance (or, prediction accuracy) of the machine learning models by calculating the out-of-sample cross-validated R-square and Mean Absolute Error (MAE) (Jarvis et al., 2022). The calculated R-squares range from 0.629 to 0.889 and the MAE is from 0.100 to 0.958 kWh (See the detailed performance of each model in Appendix C). Although the model performs well, we apply the following difference-in-differences-style estimator (Burlig et al., 2020) to take into account the prediction error:

$$\widehat{\beta}_h = E\left(Y_{i,h,post} - \widehat{Y}_{i,h,post}\right) - E\left(Y_{i,h,pre} - \widehat{Y}_{i,h,pre}\right) \tag{2}$$

where $\widehat{\beta}_h$ is the estimator of electricity flow change (changes in hourly kWh delivered from and to the grid) at hour-of-day h after the adoption of technology. $Y_{i,h,post}$ is the actual electricity flow of consumer i at hour h after adopting the technology, and $\widehat{Y}_{i,h,post}$ is the predicted counterfactuals of electricity flow at hour h after adopting the technology. $Y_{i,h,pre}$ is the actual value at hour h before adopting the technology in the training data and $\widehat{Y}_{i,h,pre}$ is the predicted value within the sample of training data. The first difference in Eq. (2) is an estimate of the treatment effect of adopting technology and the second difference is the model prediction error. Thus, by minus the prediction error in the training data, this difference-in-differences-style estimator can ameliorate the concern for the accuracy of counterfactuals prediction.

When we estimate the impact of adopting solar PV on consumer #1′s electricity sent to grid and the impact of adopting solar PV and battery on consumers #2 and #3′s electricity sent to grid, treatment effects are simply the observed amounts of kWh sent to grid one month after the technology adoption. We report these values directly without using the machine learning approach in these circumstances in Section 3.2.

This study has the limitation of the small sample size. Few consumers adopted the three technologies at the same time and our study is based on a sample of three representative early adopters. Interpreting the broader implications of our results should be cautious given that future consumers who adopt these technologies on a large scale may have different characteristics from the first adopters. Nevertheless, this paper provides a pilot study with empirical evidence of consumers' behavior changes after co-adopting the three technologies.

2.4. *Calculations of private and environmental benefits*

The coadoption could not only change electricity consumption but also changed consumers' private benefits (electricity bill savings and vehicle fuel cost savings) and environmental benefits (avoided pollution from dirty electricity generation sources and driving gasoline vehicles). Based on our estimations of electricity consumption changes, we conduct a back-of-envelope calculation on these benefits. See methodology details in Appendix E and we discuss the results in the discussion

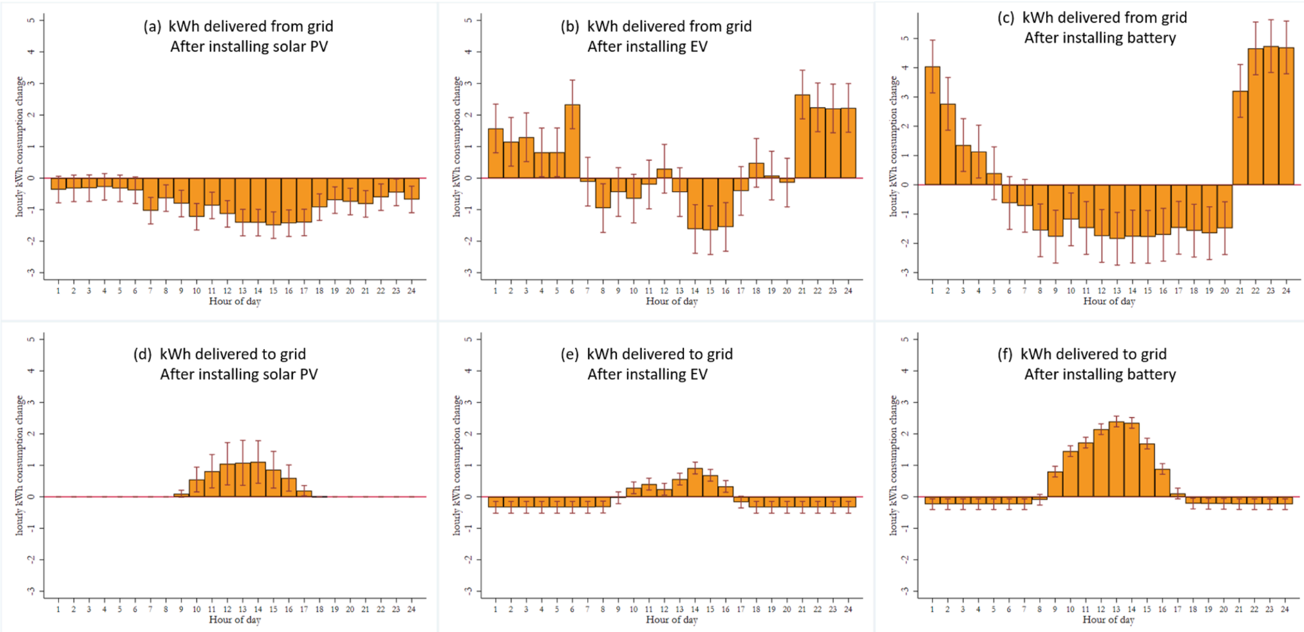

Fig. 3. The impact on treated consumer #1′s electricity consumption patterns after adopting each technology. (Note: yellow columns are point estimators, error bars in subplots (a)(b)(c)(e)(f) are 95% confidence intervals, and error bars in subplot (d) are standard deviations.).

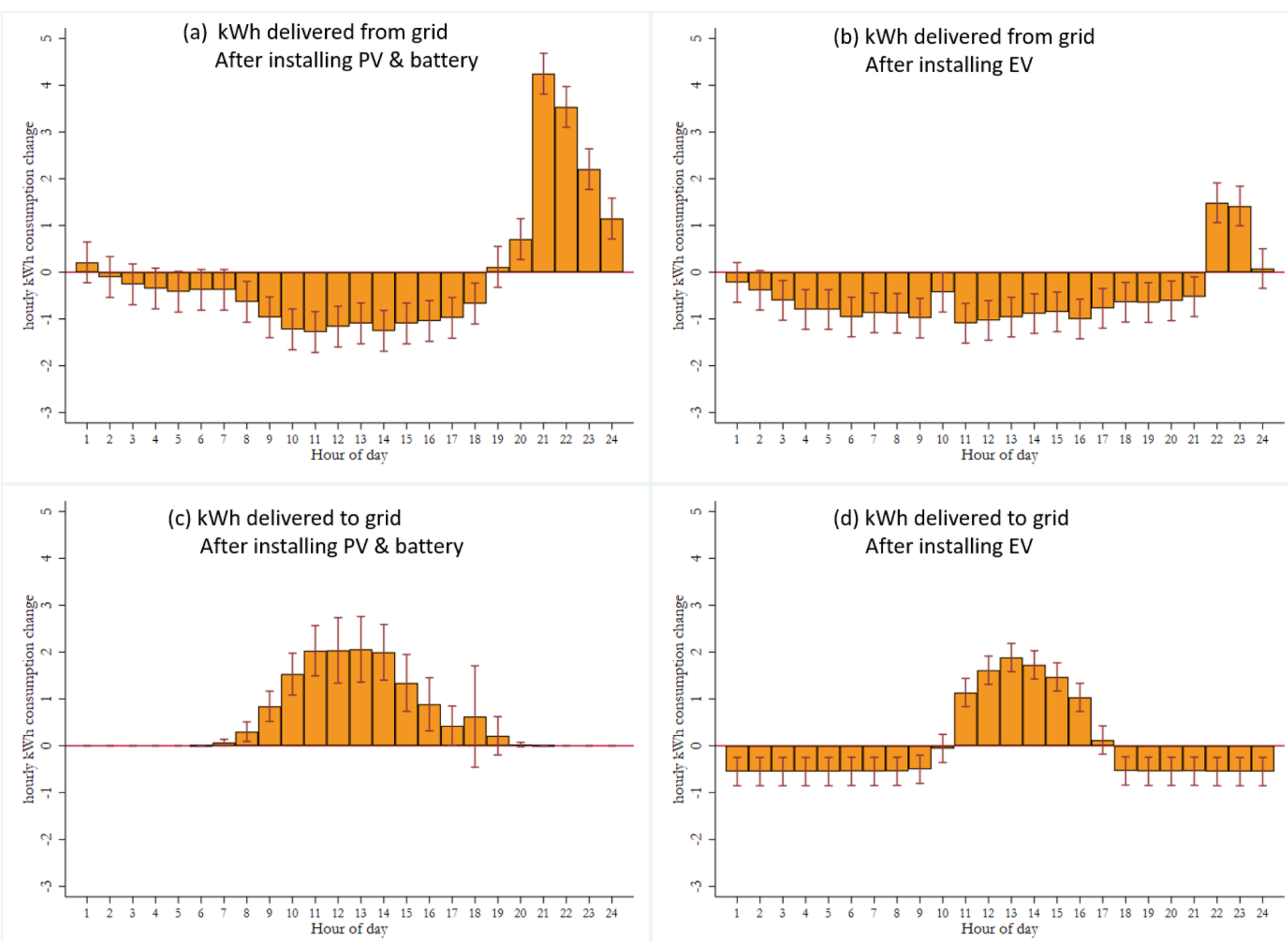

Fig. 4. The impact on treated consumer #2′s electricity consumption patterns after adopting each technology. (Note: yellow columns are point estimators, error bars in subplots (a)(b)(d) are 95% confidence intervals, and error bars in subplot (c) are standard deviations.).

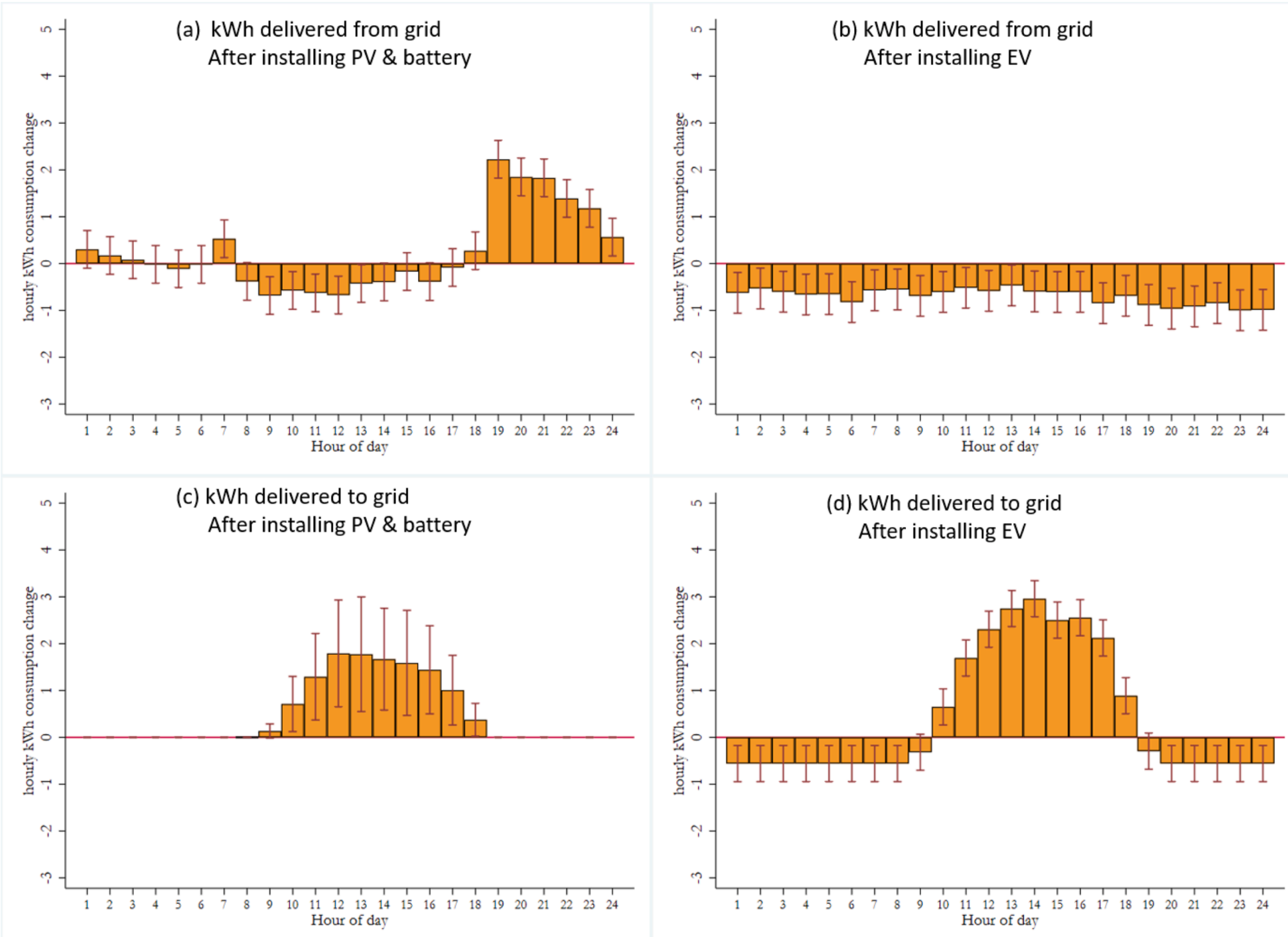

Fig. 5. The impact on treated consumer #3′s electricity consumption patterns after adopting each technology. (Note: yellow columns are point estimators, error bars in subplots (a)(b)(d) are 95% confidence intervals, and error bars in subplot (c) are standard deviations.).

section.

3. Results

3.1. The overall impact of co-adopting electric vehicles, solar photovoltaics, and battery storage

We first check the impact of co-adopting the three technologies on average hourly electricity flows using the difference-in-differences method in conjunction with matching. In our final sample of analysis, we include 3 representative early adopters accompanied by 21 comparable control users. The time-series smart meter data in our analysis include 274,457 observed hours of electric input and output. We examined three outcomes of interest, kWh delivered from the grid, kWh delivered to the grid, and net load, respectively. The estimated change in average hourly kWh delivered from the grid is 0.0005 (with the standard error of 0.28) and the estimated change in average hourly net load is -0.68 kWh (with the standard error of 0.31; see detailed estimation results in Appendix D). After installing the three technologies, the average hourly kWh delivered from the consumers to the grid is 0.68 (with the standard deviation of 1.2). It means that the co-adoption of the three technologies did not change the consumers' average hourly electricity consumption (or, daily electricity consumption) delivered from the power grid but consumers sent excess electricity back to the grid. Thus, the impact of the coadoption on net load is negative.

Second, we check the change in electricity consumption patterns by estimating the impact by 24 h of the day. Fig. 2 shows the estimated results by the three different outcomes (See detailed estimates in Appendix D). Subplot (a) shows the impact on electricity consumption delivered from the grid. We find that the treated users reduced their hourly electricity consumption from the grid significantly by about 1 kWh from 6AM to 9PM, and increased their hourly electricity consumption significantly by about 2.5 kWh from 10PM to 1AM. The positive impact (increased electricity consumption compared to periods before the technology adoption) decayed to 0 from 2AM to 5AM. The reduced consumption could be due to the generation from solar PV and the discharge from battery storage. In the hours without sunlight (e.g., 8PM to 9PM), the reduced consumption could be only due to the discharge of the battery. The significantly increased consumption in the middle of the night (10PM to 1AM) could be due to the charging of battery storage and electric vehicles. Subplot (b) shows the hourly electricity sent back to the grid. We find that the treated consumers sent excess electricity to the grid from 10AM to 5PM when the solar PV can generate electricity with sunlight. The electricity send to grid could also be due to the discharge of battery. Subplot (c) shows the overall impact on consumers' net load, which is consistent with the results in subplots (a) and (b). The consumers increased their net load significantly at late night and reduced net load during the day and early evening.

The decreased net load can save consumers' energy bills. In addition, after installing the solar PV, all the three treated users switched their rate plan to E27 consumer generation price plan, which charged electricity consumption based on time of use. Under the E27 rate plan, on-peak hours are from 2PM to 8 PM in summer and from 5AM to 9AM and from 5PM to 9PM in winter. According to our estimated result, the

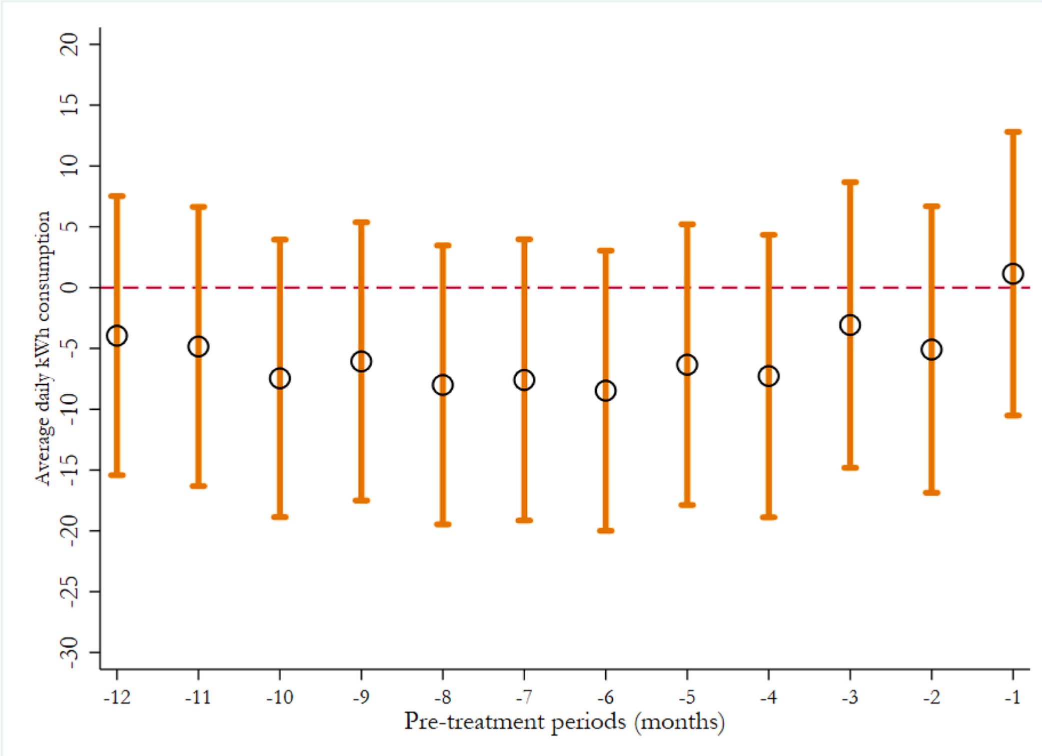

Fig. A1. Pre-treatment parallel trend test. Note: Circles are point estimators and error bars are 95% confidence intervals.

reduced consumption happened during the on-peak hours (with a higher rate) and the increased consumption happened during the off-peak hours (with a lower rate), which could further reduce the users' electricity bills (See detailed calculation of private benefits in Section 4).

To sum up, after the installation of electric vehicles, solar photovoltaics, and battery storage, the three residential consumers did not change their overall daily electricity consumption from the grid but switched their intraday consumption patterns and sent excess electricity back to the grid. That is, with the help of the three technologies, they reduced their net load during the day and early evening (including peak hours with higher electricity prices) and increased their net load during the late evening (off-peak hours with lower electricity prices), which help save energy bills, reduce grid load variability, and meet their travel needs via electric vehicles.

Peak demand is the highest electric power demand during a specific time, which determines the maximum generation capacity of power plants in order to meet the electricity consumption needs of all time periods. Shaving peak demand helps save utilities and consumers' money by lowering wholesale electricity prices and subsequent retail electricity prices as well as deferring construction of new power plants and power delivery systems that are reserved for use during peak times (US DOE, 2022). According to our results, the coadoption of these three technologies, that help shave peak demand and increase off-peak demand, is consistent with the long-term strategy of demand management of electric utilities.

3.2. Electricity consumption pattern changes after adopting each technology

To further understand the decomposed impacts of co-adopting the three technologies, we explore the changes in electricity flows (delivered from and to the grid) after each technology adoption for each individual treated user, respectively. Using the machine learning approach (Random forest algorithm), we generate the counterfactuals of electricity flows and then estimate the impact of coadoption on electricity consumption patterns within one month after the installation of each technology. As for the impact of adopting solar PV on consumer #1 and the impacts of adopting solar PV and battery on consumers #2 and #3, we directly report the average and standard deviation of hourly kWh sent back to the grid within the first month.

Fig. 3 shows the estimated changes in electricity consumption pattern of the treated consumer #1, who installed the solar PV, the electric vehicle, and the battery storage, successively. After installing the solar PV, the consumer decreased electricity consumption from the grid significantly and sent excess electricity back to the grid in the daytime because of the generation from solar PV. After installing the electric vehicle, electricity consumption from the grid was increased at night (from 9PM to 6AM), which could be due to charging the vehicle, and was decreased in the daytime, which could be due to the consumer traveling more within the first month after adopting the new electric vehicle. The increased electricity exported to the grid in the daytime could be due to the decreased electricity demand caused by the absence of a homeowner who left her/his home by car. After installing the battery storage, the electricity consumption from the grid increased at night and decreased during the day and early evening, which could be due to that charging at off-peak hours and discharging at peak hours can save energy bills, especially during the summer. In winter, the E-27 tariff gap between off-peak and peak prices is small, so there is little room for arbitrage profits given the energy loss during battery charging and discharging. Subplot (f) shows that the consumer may send electricity back to the grid through discharging the battery in the daytime (including the peak hours with high electricity rates).

Fig. 4 shows estimated impacts on the treated consumer #2, who installed solar PV and battery together at first and then adopted electric vehicle later. After adopting the PV and battery, consumer #2 increased electricity consumption from the grid significantly at night from 8PM to 12AM because of charging battery storage. During the daytime, electricity consumption from the grid decreased and exported electricity increased because of the generation of solar PV and discharging from the home battery. After installing the electric vehicle, a similar pattern

Table A1
Model performance.

		Adopting PV	Adopting EV	Adopting Battery	Adopting PV & Battery
Panel A: Outcome: kWh delivered from the grid					
		Adoption Stages			
Consumer #1	Out-of-sample CV MAE	0.415	0.549	0.958	
	Out-of-sample CV R2	0.667	0.842	0.629	
Consumer #2	Out-of-sample CV MAE		0.275		0.277
	Out-of-sample CV R2		0.834		0.855
Consumer #3	Out-of-sample CV MAE		0.363		0.370
	Out-of-sample CV R2		0.749		0.675
Panel B: Outcome: kWh delivered to the grid					
		Adoption Stages			
		Adopting PV	Adopting EV	Adopting Battery	Adopting PV & Battery
Consumer #1	Out-of-sample CV MAE		0.121	0.100	
	Out-of-sample CV R2		0.806	0.769	
Consumer #2	Out-of-sample CV MAE		0.138		
	Out-of-sample CV R2		0.889		
Consumer #3	Out-of-sample CV MAE		0.177		
	Out-of-sample CV R2		0.866		

Note: For each individual user, we use observations before the adoption of each technology as training data to train our machine learning model using the Random Forest algorithm. To validate our model, we check the model performance by calculating the out-of-sample cross-validated mean of absolute error (MAE) and R square. The training data is divided into 10 folds when implementing the cross-validation.

change is noted. The significant increase in electricity consumption from the grid at night (from 9PM to 12AM) indicates that the consumer may charge their electric vehicle at that time. The decrease in electricity consumption from the grid and the increase in exported electricity in the daytime may imply that the consumer travel more during the day.

Fig. 5 shows estimated impacts on treated consumer #3, who also installed solar PV and battery together at first and then adopted the electric vehicle later. We find consumer #3 had a similar pattern change as consumer #2 after installing the solar PV and battery. However, we fail to identify a distinct change in consumer #3′s electricity consumption from the grid after adopting the electric vehicle. It could be due to that consumer 3 did not charge their EV at home (e.g., only at public charging stations) within the first month after they bought it. The increased exported electricity to the grid during the daytime could be due to more travel and less electricity consumption demand at home. This finding also indicates that consumers may not behave as predicted due to the heterogeneity of consumers and demonstrates the importance of the empirical study.

Table A2
Estimates of difference-in-differences.

	Model (1)	Model (2)	Model (3)	Model (4)
	Outcome: kWh delivered from grid		Outcome: net load	
D	0.0005		-0.6844**	
	(0.287)		(0.3138)	
D_hour1		2.011		2.003
		(1.347)		(1.342)
D_hour2		1.431		1.424
		(1.065)		(1.060)
D_hour3		0.892		0.885
		(0.765)		(0.760)
D_hour4		0.475		0.467
		(0.533)		(0.528)
D_hour5		0.156		0.149
		(0.408)		(0.403)
D_hour6		-0.818***		-0.831***
		(0.0775)		(0.0731)
D_hour7		-0.935***		-0.949***
		(0.0730)		(0.0698)
D_hour8		-1.068***		-1.115***
		(0.112)		(0.119)
D_hour9		-1.119***		-1.420***
		(0.143)		(0.218)
D_hour10		0.0113		-0.982***
		(0.0919)		(0.108)
D_hour11		-0.328		-2.157***
		(0.278)		(0.330)
D_hour12		-0.727***		-3.222***
		(0.0538)		(0.0631)
D_hour13		-0.766***		-3.460***
		(0.0856)		(0.0701)
D_hour14		-0.760***		-3.411***
		(0.102)		(0.0825)
D_hour15		-0.777***		-3.069***
		(0.142)		(0.0817)
D_hour16		-0.747***		-2.495***
		(0.114)		(0.164)
D_hour17		-0.733***		-1.665***
		(0.0939)		(0.258)
D_hour18		-1.066***		-1.341***
		(0.235)		(0.184)
D_hour19		-1.058***		-1.103***
		(0.203)		(0.205)
D_hour20		-1.107***		-1.124***
		(0.159)		(0.164)
D_hour21		-0.627**		-0.644**
		(0.237)		(0.235)
D_hour22		2.122***		2.113***
		(0.487)		(0.486)
D_hour23		3.382**		3.374**
		(1.475)		(1.471)
D_hour24		2.161		2.153
		(1.333)		(1.328)
Adjusted R-squre	0.26	0.29	0.25	0.32
Observations	274,457	274,457	274,457	274,457

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors are in parentheses and clustered at the individual consumer level. Control variables include spline function of hourly temperature, year fixed effects, month-of-year fixed effects, season-by-hour-of-day fixed effects, day-of-week fixed effects, and national holiday fixed effects.

To sum up, these identified electricity consumption pattern changes after each individual technology adoption are consistent with our estimated overall impact of co-adopting the three technologies.

4. Discussion and conclusion

Electric vehicles, solar photovoltaics, and battery storage play an important role in electrification, clean power grid, and deep decarbonization. As the penetration rate of these three technologies keeps increasing, understanding their impact on the power grid and consumer behavior changes becomes more important. Particularly, the impact of co-adopting the three technologies can be different from a simple combination of adopting three different technologies independently. This study provides the first empirical evidence of the impact of co-adopting these three technologies on residential electricity consumption patterns in Arizona. While there was no significant change in average hourly (or daily) electricity consumption delivered from the grid after installing the three technologies, we find that consumers changed their intraday consumption patterns by reducing consumption from the grid during the day and early evening, increasing consumption from the grid at late night, and exporting excess electricity back to the grid during the day (see detailed changes in Fig. 2). The average hourly net load of the three treated consumers decreased by 0.68 kWh after installing the three technologies. Our decomposition analysis suggests four behavior patterns: (1) Users applied the solar PV to generate electricity during the day, which reduced consumption from the grid; (2) Users charged residential batteries in the late night and early morning (off-peak period with lower electricity prices) and discharged during the day and early night (including an on-peak period with higher electricity prices); (3) Users charged electric vehicles in the late night and early morning; (4) Users sent excess electricity back to the grid during the day through solar generation and discharging home battery.

The average electricity consumptions of the early adopters in our sample are similar to average consumers in Arizona (see Table 1). Thus, our selected sample could be representative. Although this paper is limited by the small sample size, we still provide implications about the general consumption pattern changes for the broader population. One caveat is that our findings apply for the specific case of Arizona and similar climates, and that the coadoption may have different impacts in zones with different consumption peak times.

This paper provides several implications for utilities, policymakers, and environmental communities. First, consumers, who co-adopt electric vehicles, solar photovoltaics, and battery storage, tend to reduce their electricity consumption from the power grid during peak hours and increase their consumption during off-peak hours. This consumption pattern change helps reduce peak energy demand and adds off-peak demand contributing to a more reliable and affordable electric grid. Our findings provide new documented benefits of co-adopting the three technologies. Policymakers should provide more incentives, such as rebates, low-interest loans, tax credits, and alternative business models, to encourage adopting them. Second, our analysis indicates that coadoption brings significant private and environmental benefits through changing intraday electricity consumption patterns and avoiding driving gasoline vehicles. The calculated annual private benefits associated with the coadoption are $2646 per household and the associated annual environmental benefits range from $340 to $664 per household. (See the detailed estimation of benefits in Appendix E). Policymakers can initiate information programs about the benefits to encourage co-adopting the three technologies. Third, although we find net positive environmental benefits after adopting these technologies, increased electricity consumption at night when the marginal damage of electricity generation is higher leads to environmental damage. Policymakers should apply more approaches to fully decarbonize the power grid as we move further up the level of electrification. For instance, we should phase out coal power plants in the U.S. as soon as possible to reduce reliance on coal to satisfy marginal electricity use (Holland et al., 2022). Fourth, in addition to providing subsidies and information to encourage co-adopting these three technologies, utilities and policymakers can also encourage more consumers to apply the time-of-use rate plan, which provides additional incentives for the coadoption.

This study has limitations. Few consumers adopted the three technologies at the same time and our study is based on a sample of three representative early adopters. Interpreting the broader implications of our results should be cautious given that future consumers who adopt these technologies on a large scale may have different characteristics from the first adopters. Nevertheless, this paper provides a pilot study with empirical evidence of consumers' behavior changes after co-adopting the three technologies.

The electricity consumption patterns after adopting these technologies are determined by consumers' motivations and use strategies (such as self-sufficiency and minimizing electricity bills). It helps understand consumers' motivations by comparing the calculations of simulation-based optimization with our empirical estimates. However, since we cannot observe the installed size of solar PV and home battery, we cannot infer the optimal electricity consumption pattern. Although this analysis is beyond the scope of our paper, it could be an important extension in future studies.

Future empirical studies can keep investigating the impact of co-adopting clean technologies on consumer behaviors with an increasing number of consumers adopting them. With the data of solar generation, future studies can estimate the impact of coadoption on consumers' energy consumption and identify whether there is a rebound effect after the coadoption. In addition to quantitative studies, more qualitative or interview-based analyses can be conducted to actually ask the users what they are doing with the three technologies. With more data of consumers' attributes at the individual level, future studies can also explore the linkage between heterogeneous behavior changes after the technology adoption and the heterogeneous consumer attributes (e.g., income, political leanings, marginalized groups).

Data statement

The high-frequency smart meter data were obtained from the Salt River Project. The data are proprietary and are not publicly available under a non-disclosure agreement with Salt River Project. The hourly temperature data in the city of Phoenix were obtained from the website of the National Oceanic and Atmospheric Administration (https://www.ncdc.noaa.gov/cdo-web/).

CRediT authorship contribution statement

Xingchi Shen: Conceptualization, Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing. **Yueming Lucy Qiu:** Conceptualization, Funding acquisition, Supervision, Validation, Writing – review & editing. **Xing Bo:** Validation, Writing – review & editing. **Anand Patwardhan:** Supervision, Validation, Writing – review & editing. **Nathan Hultman:** Supervision, Validation, Writing – review & editing. **Bing Dong:** Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Data availability

The data that has been used is confidential.

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Appendix A. Residential electricity rate plans of the SRP utility

Plan number	Plan name	Season	On peak hour marginal rate ($/kWh)	Off peak hour marginal rate ($/kWh)	Notes:
E-21	Super peak Time-of-Use	Summer	0.2924	0.0858	On-peak hours are 3- 6 p.m. Monday to Friday and the rest are off-peak hours
		Summer peak	0.3473	0.0882	
		Winter	0.1110	0.0785	
E-27	Customer generation price plan	Summer	0.0491	0.0389	On-peak hours are 2- 8 p.m. in summer and 5–9 a.m. & 5–9 p.m. in winter, Monday to Friday. The rest are off-peak hours.
		Summer peak	0.0651	0.0441	
		Winter	0.0457	0.0417	
Plan number	**Plan name**	**Season**	**Flat rate ($/kWh) (0–2000 kWh)**	**Flat rate ($/kWh) (2001+ kWh)**	
E-23	Standard price plan	Summer	0.1120	0.1163	
		Summer peak	0.1186	0.1299	
		Winter	0.0829	0.0829	

Note: Summer is defined as May, June, September, and October. Summer Peak is defined as July and August. Winter is defined as the November through April billing cycles. We only report the rate plans applied by the sampled users in this study. See other rate plans on the website of SRP utility company: https://www.srpnet.com/menu/electricres/priceplans.aspx.

Appendix B. Pre-treatment parallel trend test

To formally test the pre-treatment parallel trend assumption, we group all the matched users, restrict the dataset to the pre-treatment period only, and regress average daily consumption within each month on the interaction terms between a treatment group dummy variable and the indicators of 12 months prior to the treatment controlling for individual user fixed effects, year fixed effects, and month of year fixed effects (following Muehlenbachs et al. (2015)'s approach). Regression results show that all the estimated coefficients are close to zero and not significant statistically (See the figure below), which indicates that there are no differential trends between the treated and control groups prior to the treatment. Fig. A.1.

Appendix C. Model performance of machine learning

Table A1

Appendix D. Estimates of electricity consumption change after installing the three technologies

Table A2

Appendix E. Private and environmental benefits

The coadoption of the three technologies and the electricity consumption pattern change may bring changes in private benefits and environmental benefits. In this section, we conduct a back-of-envelope analysis of the benefits.

We first calculate the private benefits (energy bill savings), which include electricity bill savings and vehicle fuel cost savings. We assume that consumers' rate plan is fixed to E27 (customer generation price plan) before and after installing the three technologies[4] and the resulting estimated annual electricity bill savings caused by the electricity consumption pattern change is $286 per household. We estimate the vehicle fuel cost savings as equal to the gasoline costs of a typical gasoline car in the U.S.[5] so the annual vehicle fuel cost savings are $2360. Thus, the total annual private benefits caused by co-adopting these three technologies are $2646 per household.

The environmental impacts include the avoided environmental damage of electricity generation and the avoided environmental damage of driving a gasoline vehicle. Electricity generation emits air pollutants, such as CO_2, SO_2, NO_X, and PM2.5. To account for the benefits of avoided CO_2 emissions by electricity generation, we obtained the value of marginal CO_2 emissions by hour of the day in the West Electric Power Interconnections from (Holland et al., 2022) and multiply it by the value of Social Cost of Carbon (SSC) to get the value of hourly marginal damage to the environment per kWh of electricity generated. Based on the standard approach from the U.S. Environmental Protection Agency (EPA, 2021), the SSC in 2020 ranges from $14 to $152 per metric ton of CO_2 depending on different discount rates. We then obtain the values of local marginal damage of SO_2, NO_X, and PM2.5 emissions by hour of the day in the Western Electricity Coordinating Council region from (Holland et al., 2016). By multiplying the changed hourly net load (kWh) with the hourly marginal damage, we get the avoided environmental damage. The annual avoided environmental damage caused by electricity consumption pattern change ranges from $47 to $371 per household. Avoiding driving a gasoline vehicle can bring environmental benefits by avoiding air pollutant emissions. According to Holland et al. (2019), the environmental damage (without carbon emissions) from driving gasoline cars in Phoenix is 1.93 cents/mile, while the cost of carbon emission is 0.24 cents/mile from driving gasoline cars based on estimates

[4] In our sample of the three treated consumers, two consumers changed their rate plan from E23 to E27 and one consumer changed their plan from E21 to E27 after installing the solar PV. For simplicity, here we assume the consumers' rate plan is fixed to E27 and calculate their energy bill savings caused by the electricity consumption pattern change. We multiply the changed hourly net load with hourly electricity prices by different seasons (summer, summer peak, and winter) to obtain hourly savings, and then add them up to annual savings.

[5] According to U.S. Department of Transportation's Federal Highway Administration (2018), people in the U.S. drive 13,500 miles a year on average. A typical gasoline vehicle in the U.S., Ford F-150, gets 24 miles per gallon of gas. That means the average gasoline consumption of a typical vehicle is 562 gallons. According to EIA (2022), the average retail gasoline price on April 2022 is $4.2 per gallon. Thus, the annual cost of gasoline consumption by a typical vehicle in the U.S. is $2360.

from (Parry et al., 2007). The avoided annual environmental damage of a typical gasoline vehicle[6] is $293. Thus, the total annual avoided environmental damage ranges from $340 to $664 per household.

Although these three technologies bring private and environmental benefits, co-adopting these technologies incurs costs. Consumers need to spend money to install the solar PV and the home battery and spend extra money to purchase an electric vehicle which is usually more expensive than a traditional gasoline vehicle. Detailed estimations on the co-adoption costs are beyond the scope of this paper, but the payback period after investing in these three technologies can be a key parameter that determines whether consumers are willing to install them.

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[6] According to U.S. Department of Transportation's Federal Highway Administration, people in the U.S. drive 13,500 miles a year on average. 13,500 miles* (0.0193$/miles+0.0024$/miles) = 293$.