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Impacts of the co-adoption of electric vehicles and solar panel systems: Empirical evidence of changes in electricity demand and consumer behaviors from household smart meter data

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ABSTRACT

During the electrification of household energy consumption, there is an increasing number of consumers that purchase both electric vehicles (EV) and distributed solar photovoltaics (PV) systems. This study aims to examine the change in electricity demand from the power grid for EV owners when they add distributed solar panels to their homes. The impacts of the two technologies combined are different from the sum of two individual impacts because they may not be additive and EV consumers' behaviors may be subject to change. We apply a difference-in-differences model and compare consumers with or without EVs and also EV consumers with and without additional PVs. We use the hourly electricity demand data for 13,190 households in the Phoenix metropolitan area in Arizona. Our results show that EV consumers, without PV panels, use more electricity compared to non-EV consumers, and their average hourly demand is higher by 0.4 kWh. After adding PVs, EV consumers decrease the average hourly demand from the electric grid by 1.1 kWh. The co-adoption of PVs with EVs helps reduce the system peak hour loads. Besides, we also find evidence of behavior changes when EV consumers shift some of their EV charging from night to day so that they are charging their EVs with more cleaner electricity. The annual monetary savings for consumers after adding PVs are estimated to be ~\$930, and the total social savings are estimated to be ~\$925. Given the positive co-adoption effects, a policy implication is that incentives should be provided to promote the co-adoption of PVs with EVs.

1. Introduction

The adoption of electric vehicles (EVs) has increased rapidly due to many initiatives in transportation electrification (Needell et al., 2016; Muratori, 2018; Knobloch et al., 2020). It is also a trend that an increasing number of consumers are purchasing both EVs and distributed solar photovoltaics (PV) systems (Delmas et al., 2017; Li et al., 2017). The penetration of EVs together with a cleaner electric grid can mitigate greenhouse gas emissions and reduce pollutants from petroleum-driven cars (Muratori, 2018; Jenn, 2020; Xing et al., 2021). If EVs are charged with renewable solar energy, less electricity generated from fossil fuels will be required. The distributed solar panels generate cleaner electricity while EV batteries can be used to store the solar-generated electricity. Meanwhile, the combination of EVs with PVs also potentially impacts the supply of the electricity sector by reshaping the electricity loads (Burkhardt et al., 2019).

We examine the impacts of the two technologies together—EVs and PVs—rather than the impacts of EVs and solar systems individually. The impacts of these two technologies may not be additive and EV charging behaviors may be subject to change after solar panels are added. Consumers may adapt EV charging to the variable solar energy generation and shift EV charging to the hours when solar panels are generating electricity. Studies have already shown that behavioral changes may occur after solar panel adoption. Consumers may use more electricity when the marginal cost for electricity generation becomes tiny (i.e., the rebound effect) (Roy, 2000; Qiu et al., 2019). However, to our knowledge, no studies have specifically focused on the behavioral changes that occur when EVs and distributed PVs are both adopted by consumers, and this study will provide such an analysis to empirically assess the impacts of this co-adoption.

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The co-adoption of EVs and PVs also influences the electric loads of the grid. EVs could facilitate the integration of solar generation into the grid by increasing the local consumption of solar electricity and absorbing the solar generation that would otherwise be curtailed (Finn et al., 2012; Denholm et al., 2013; Richardson, 2013; Mwasilu et al., 2014; Fares and Webber, 2017; Hoarau and Perez, 2018). Moreover, the co-adoption possibly helps with reducing system peak loads because it reduces EV charging during early evening hours (Muratori, 2018; Burlig, 2020), which coincide with system peak hours (e.g., 2–8 p.m. in Arizona) (Novan and Smith, 2018; Burkhardt et al., 2019). Our study provides the first empirical evidence of the changes in electricity consumption behaviors of EV consumers after adopting solar panels. Our findings could help with the electric load analysis (Wang et al., 2019) and provide guidance for load management strategies. They also have implications for future power infrastructure investments given that system peak loads determine the required generation and transmission capacity.

This study focuses on the co-adoption of EVs and residential solar PVs in Phoenix, Arizona, using smart meter data of about 13,190 households during 2013–2019 from a large utility company. We employ a difference-in-differences strategy that captures the pre- and post-treatment differences in electricity demand and also compares the treated with the control groups. Our panel regression analyses using the hourly smart meter data have the benefits of accounting for the hourly heterogeneity and providing more reliable estimates (e.g., by reducing the impact of omitted variables) (Ghanem and Smith, 2021). This analysis using hourly data is also more precise for estimating environmental damages because the marginal emissions factors from the electric grid differ by hour-of-day due to the various marginal fuels being used for electricity generation.

There is a self-selection issue for EV and PV adoption in this study. The adopters share some characteristics that make them more likely to sort into the adoption than others. Our attempts to reduce the self-selection bias include (1) We have separated the consumers into two comparison groups— control consumers (non-EV non-solar consumers) vs. EV-only consumers and EV-only consumers vs. co-adoption consumers, and we focus on the impacts of EVs and additional PVs (co-adoption) individually. (2) We have included individual-consumer fixed effects, which tease out the time-invariant differences such as education, household income, and environmental awareness. In addition, we have added zip code-by-year fixed effects in Section 5.3.2, which controls for the unobservables that change at the zip code level across years. (3) We have added a two-stage model, as the best as we can, as one more robustness check.

Our results show that consumers use more electricity after EV adoption, and their hourly demand is higher by 0.4 kWh, on average. After adding PVs, EV consumers decrease the average hourly demand from the electric grid. The co-adoption of EV and solar panels also helps reduce the system peak hour loads (2–8 p.m.). In addition, we also find evidence of behavior changes where EV consumers shift some of their EV charging from night to day when solar panels are generating electricity. Thus, EV consumers are charging their EVs with cleaner solar electricity – both an environmentally-driven and environmentally beneficial behavior change. Our findings are robust to alternative model specifications and show consistency with the main results. Finally, additional PV adoption leads to similar private and social savings. The annual private savings for consumers after adding PVs are estimated to be ~ $930 (or 9866 kWh), and the annual total social savings are estimated to be ~$925.

This paper begins by providing a theoretical framework in Section 2. Section 3 describes the data that are used to identify the effects of EVs and additional PVs. Sections 4 and 5 provide the empirical analysis, present the results, and show the robustness checks. Sections 6 and 7 estimate the private and social benefits resulting from co-adoption of PVs with EVs, discuss the policy implications, and also conclude.

2. Theoretical framework

In this section, we provide a theoretical framework to conceptualize the possible consumption behavior changes of EV customers after adding PVs. For this study, residential electricity consumption is considered a normal good. We divide the electricity consumption into peak hour demand and non-peak hour demand. We assume that there is measurable substitution elasticity between peak and non-peak demands (Filippini, 1995; Baladi et al., 1998). We also assume potential changes brought out by battery technology are not likely to be very large given that residential battery storage is not widely adopted during our study period (2013–2019) (Qiu and Xing, 2020).

As illustrated by figure panel (a), the peak and non-peak hour demand are perceived as two products substitutable to each other to a certain degree during a day. The equilibrium level of peak hour demand is at Q_1 while that for non-peak hour is at Q_2. Figure panel (b) illustrates how the electricity demand will change if the budget line for the consumers changes. After adding solar panels, the electricity bills reduce, which has an equivalent effect of reducing average electricity prices. Although the average prices for both the peak hours and non-peak hours reduce, the price for the peak hours (2-8 p.m.) reduce more given that their original prices are higher (Table A1 in the Appendix[1]). The equilibrium moves from product bundle A to B. The equilibrium level of peak hour demand increases to Q_1' while that for non-peak hour reduces to Q_2'.

Figure panel (c) shows how consumers' preference for solar electricity changes their electricity demand.[2] Consumers may consider energy generated from solar more environmental-friendly or "greener" compared to the electricity generated from fuel fossils (Nienhueser and Qiu, 2016; Deng and Newton, 2017; Qiu et al., 2019). Therefore, consumers tend to consume more during peak hours which coincide with many hours of solar generation. With this change in the indifference curve, the equilibrium moves from product bundle A to C. The peak hour demand increases to Q_1' while that for non-peak hour decreases to Q_2'. In the case of (d), there are both changes in consumers' income level and preference, and thus both the budget line and indifference curve change. The equilibrium moves from product bundle A to D. A new equilibrium is reached at (Q_1', Q_2').

In the following empirical section, we will examine how EV consumers' hour-by-day electricity demand changes after the solar panels are added. Their electricity consumption behaviors may be subjected to income effects when solar installation changes (or is perceived to change) the electricity bills they pay. The EV consumers may also have different preferences given that solar energy generation is considered more environmental-friendly. Our empirical analysis examines both potential income effects and preference effects on electricity consumption behaviors.

[1] Almost all of our solar consumers are on regular net metering plans with a few exceptions. These net-metering consumers pay a monthly demand charge and also a kWh charge lower than other standard plans. We do not differentiate them in the theoretical model, and assume that they behave in similar ways as those on other standard electricity plans. No matter what plans the consumers are on, solar panels all reduce their electricity bills. Their responses to solar adoption should be in the same direction, although the magnitudes may differ.

[2] The consumers that add PVs may have different indifference curves ex ante than the general consumers. Due to this self-selection, a general consumer may have a slightly different magnitude of preference change after solar adoption than what we have plotted in the figure.

3. Data

We obtain data from a major utility company called the Salt River Project (SRP[3]) in Phoenix, Arizona. The SRP consumers self-reported their EV ownership and their EV charging through an internal load impact study, in which financial incentives were provided for reporting. For these EV consumers, we have information on the electricity rate plans, the EV starting charging dates, the levels of chargers (level 1 and level 2), and the number of registered electric vehicles.[4] The smart meter data for EV owners is from May 2013 to April 2019, and it records consumers' hourly electricity demand. The smart meter data for non-EV non-PV consumers spans from January 2014 to April 2019. The solar generation starting dates for consumers can be identified by the way their meter types are symbolized in the datasets. Fig. 2 plots the distribution of EV charging and solar starting dates.[5] The final dataset compiles information for 13,190 households, among which 1805 are EV-only consumers and 320 are co-adoption consumers of EVs and solar panels. The electricity prices charged to the consumers are displayed in Table A1 in the Appendix. The distribution of consumers on different electricity price plans is also displayed in Fig. A1.

We divide the consumers into two comparison groups: (1) control consumers (non-EV non-solar consumers) vs. EV-only consumers; (2) EV-only consumers vs. co-adoption consumers (additional PV adoption after adopting EVs). Fig. 3 plots the net delivered electricity (kWh delivered from the electricity grid to the consumer minus the kWh sent back to the grid from the solar consumer). Figure panel (a) depicts how net delivered electricity demand changes before and after EV adoption. It shows that EV-only consumers (red line) have higher electricity demand, on average, than non-EV-non-solar consumers (blue line), especially during the night hours (7 p.m.-5 a.m.). Figure panel (b) compares the electricity demand before and after adopting additional PVs (all have adopted EVs). For co-adopters (red line), their average hourly demand is much lower because of solar electricity generation, especially during the day hours (7 a.m.-7 p.m.). The net delivered electricity is even negative from 10 a.m.-3 p.m. when solar panels send more electricity back to the grid than their electricity consumption. For more comparison, we also plot the electricity demand for consumers with three different adoption statuses: before adopting an EV, after the EV but before solar, and after the EV and solar (Fig. A2). This figure further shows that the increase after the EV is greater than the decrease after solar during night hours (7 a.m.- 7 p.m.), providing some descriptive information on the magnitudes of changes.

4. Empirical strategy

We apply a difference-in-differences (DID) model to the comparison between the following groups: control consumers vs. EV-only consumers and EV-only consumers vs. co-adopters. The first comparison is used to control for the baseline impact of EVs while the second comparison group is particularly of interest to us since it helps to analyze whether additional adoption of PVs changes the behaviors of EV consumers. The following empirical model is applied for the first comparison:

$$Demand_{idh} = \alpha_i + \sum_{h=1}^{24} \beta_1^h EV_{id}{}^* hour_h + \boldsymbol{X}_{\boldsymbol{idh}}^{'}\boldsymbol{\theta} + \delta_y + \tau_m + \varphi_h + \varepsilon_{idh} \tag{1}$$

where $Demand_{idh}$ denotes consumers' net electricity demand in kWh for household i on day d at hour h. EV_{id} is equal to 1 for EV-only consumers after they purchase EVs and is 0 all otherwise. The covariates $\boldsymbol{X_{idh}}$ include hourly electricity price, Cooling Degree Days (CDD), Heating Degree Days (HDD), and two dummy variables referring to holiday or weekend days. CDD and HDD are based on the hourly temperatures obtained from (NOAA (National Oceanic and Atmospheric Administration), 2019). The coefficient β_1^h measures the change in hourly electricity load at hour h after adopting EVs and it is the key coefficient of interest. α_i represents the individual consumer-level fixed effects, which controls for time-invariant characteristics among households such as building attributes and consumer environmental awareness. The year fixed effects δ_y, month-of-sample fixed effects τ_m, and hour-of-day fixed effects φ_h are a series of time fixed effects used to capture the time-varying variation among different years, months, and hours such as the enforcement of local energy policies and economic growth. Since sampling of our data is clustered at the consumer level, we cluster the standard errors at the individual consumer level.

In addition, the following model is applied for the comparison between EV-only consumers and co-adopters. This second comparison helps to identify the impacts of additional PVs.

$$Demand_{idh} = \alpha_i + \sum_{h=1}^{24} \beta_2^h PV_{id}{}^* hour_h + \boldsymbol{X}_{\boldsymbol{idh}}^{'}\boldsymbol{\theta} + \delta_y + \tau_m + \varphi_h + \varepsilon_{idh} \tag{2}$$

where PV_{id} is 1 for the co-adopters after adopting PVs and is 0 all otherwise. Other variables are defined the same way as those in Eq. (1). All the consumers are post-EV adoption in this model. The standard errors are also clustered at the individual consumer level.

5. Results

5.1. Event study analysis

Before a DID analysis is conducted, the underlying assumption of the parallel trend between the treated and the control consumers should be satisfied. This assumption requires that before the treatment, the difference between the treatment and control groups are constant over time. If these two groups of consumers have a parallel trend, we can rule out the possibility that they might have experienced other major changes when they get the EV/PV treatment (Davis et al., 2014). We conduct an event study analysis to test the parallel trend assumption. The event study model specification is as follows:

$$Demand_{id} = \alpha + \sum_{j=2}^{J} \beta_j (Lag\, j)_{id} + \sum_{k=1}^{K} \gamma_k (Lead\, k)_{id} + \boldsymbol{X}_{\boldsymbol{id}}^{'}\boldsymbol{\theta} + \mu_i + \delta_y + \partial_m + \varepsilon_{id} \tag{3}$$

where J and K are lags and leads that are months away from the event occurrence. The baseline omitted case is the first lag where $j = 1$. $\boldsymbol{X_{id}}$ are time-varying covariates, including average electricity prices, CDD, and HDD. μ_i, δ_y and ∂_m are individual consumer-level fixed effects, year and month fixed effects. ε_{id} is the error term. Hypothetic treatment dates are assigned to the control group.

Fig. 4 panel (a) describes the effect of EV adoption on average hourly electricity demand, and panel (b) plots the effect of additional PV adoption. The x-axis indicates months before and after EV adoption (panel a) or PV adoption (panel b). The y-axis shows the changes in average hourly demand in kWh. Panel (a) indicates that prior to the

[3] SRP (Salt River Project) is one of the largest utilities in the Phoenix metropolitan area, Arizona. The utility service territory is assigned for the neighborhoods although consumers have limited ability to choose their energy providers. Nearly all houses in SRP territory have smart meters and the penetration of smart meters is quite high in Arizona. With smart meters being the standard and extra fees being charged ($20 monthly for manual reading), only a few SRP consumers were reported to choose to opt-out.

[4] We can also match these consumers with the Residential Equipment and Technology (RET) survey, conducted also by the SRP utility in 2017. The RET survey provides data on consumers' socio-demographics and housing characteristics. However, only a very small portion (<5% of all EV consumers) can be matched with the RET survey.

[5] We identify our solar starting dates based on our smart meter data. However, there are 125 consumers with solar panels installed earlier than 2013 May when smart meter data started. For these consumers, we only have their post-solar installation data.

adoption of EVs, the EV (blue line) and non-EV consumers (red line) share a similar trend. That is, the changes in the average hourly electricity consumption are not statistically different from zero for both types of consumers, which confirms the parallel trend assumption between EV consumers and non-EV consumers. In addition, after EV adoption, the hourly electricity demand for the EV consumers increases while there is no increase for the non-EV consumers. This provides suggestive evidence of increased demand after EV adoption.

Panel (b) shows that the changes in average hourly demand are not statistically different from zero before PV adoption although it fluctuates around zero.[6] This also confirms that the consumers with additional PVs and those without PVs show generally parallel trends. However, after the additional PV adoption, the average hourly demand decreases for consumers with additional PVs (blue line), but remains statistically not different from zero for the control consumers (red line). This provides suggestive evidence of decreased demand after PV adoption.

It seems that the increase in electricity demand for EV adopters is fading away (Fig. 4 panel a). There are three possible reasons for this. Firstly, it is possible that EV adopters discontinue their driving of EVs, which may be caused by dissatisfaction with the convenience of charging or having other cars (Hardman and Tal, 2021). Secondly, there may be learning-by-using for EV consumers. As EV owners have more knowledge on free public charging and workplace charging, their at-home charging is decreased. Thirdly, other medium/long-term changes could happen, such as the adoption of energy-efficient measures in the households. These measures reduce the electricity demand of EV adopters, which we may fail to capture accurately in this analysis.

In Fig. 4 panel (b), the impacts of solar adoption also seem to vary slightly over time and the following reasons could be responsible. Firstly, solar technology is advancing and solar PVs could help people save more. This is confirmed by the findings that actual savings from solar PVs are increasing slightly over years (Fikru, 2019). Secondly, there is learning-by-doing and solar consumers are learning to save more, for example, by behaviors of load shifting (Luthander et al., 2015). Lastly, there may also be some med- and long-term changes, which we fail to capture after more than one year following the solar installation.

5.2. DID results

In this section, we present our DID results based on Eqs. (1) and (2). Fig. 5 panel (a) shows the changes in electricity demand after adopting EVs. Panel (b) displays additional changes in electricity demand after adopting PVs when consumers have already adopted EVs. According to panel (a), EV consumers use more electricity compared to non-EV consumers, and their average hourly demand is higher by 0.4 kWh. The largest increase for EV consumers is 1.2 kWh, which happens at 12 a.m. There is a demand increase from 5 p.m. in the early evening to 5 a.m. in the early morning, which also indicates EV consumers tend to charge their EVs at night. This is consistent with the findings of existing literature (e.g., Burkhardt et al., 2019; Jenn, 2020). These night hours (5 p.m.-5 a.m.) also include many peak load hours (2–8 p.m.). Thus, EV adoption could further increase the peak load during these hours. The details of the coefficients in the figures are displayed in Table A2.

Panel (b) shows that after adding PVs, EV consumers' net electricity demand has decreased all across the day because of solar generation. The average decrease in hourly electricity demand is 1.1 kWh after PV adoption. The largest decrease is 2.8 kWh, which occurs at 1 p.m. The negative net delivered electricity demand across the day indicates that the solar generation is greater than the electricity delivered from the electric grid. There is extra electricity generated from solar, which can be used to meet residential demand other than charging EVs.

Interestingly, with additional solar panels, EV consumers also have decreased electricity demand during the night hours (7 p.m.-7 a.m.) when solar panels are not generating electricity. This may be due to behavioral changes of EV consumers where they shift some EV charging at night to during the day when solar panels are generating electricity. Recall that solar electricity can be considered environmental-friendly, and EV consumers might prefer to charge their EVs more with solar electricity during the day. This is consistent with our theoretical framework in Fig. 1 panel (c) where consumers' preferences change between charging their EVs with grid electricity versus with solar electricity. The details of the coefficients are displayed in Table A2.

Additionally, the co-adoption of EVs and solar helps reduce the system peak hour loads (2–8 p.m.). The adoption of battery storage could partially explain this decrease. However, only about 15% of the solar consumers have battery storage, according to the RET survey conducted by the same utility for its consumers (not exactly the same consumers sampled in this study). The remaining decrease in peak loads is explained by the concurrency of solar generation (7 a.m.-7 p.m.) and peak hour demand (2 p.m.-8 p.m.), and also explained by the potential behavioral responses of consumers (i.e., shifting EV charging from the night to the day). While uncoordinated EV charging during the day increases peak demand (Denholm et al., 2013), this study shows that the co-adoption of EVs and PVs could reduce the peak demand. This helps mitigate the need for future investments in the electricity generation infrastructure, which is necessary for meeting increased peak demand.

5.3. Robustness checks

5.3.1. Zip-year fixed effects

We conduct another analysis that includes the zip-year fixed effects as one way of robustness check. This analysis is used to control for more unobserved changes at the zip code level across different years, such as climate changes and energy initiatives at the zip code level. The results (Fig. 6) are generally consistent with the former main results in Section 5.2, which suggest that there is increased electricity demand during the night hours for EV consumers (panel a), and co-adoption consumers of EVs and solar panels have decreased their demand during the noon hours while their demand during the peak hours also decreases (panel b).

5.3.2. A second DID analysis

In this section, we try another DID analysis to examine the co-adoption impacts. While in Eq. (2), all the consumers are post-EV adoption, this secondary DID analysis also includes a comparison between pre- and post-EV adoption. The model specification is as follows:

$$Demand_{ihd} = \alpha_i + \sum_{h=1}^{24} \beta_1^h EV_{id} * hour_h + \sum_{h=1}^{24} \beta_2^h PV_{id} * hour_h + \sum_{h=1}^{24} \beta_3^h EV_{id} * PV_{id} * hour_h + \boldsymbol{X}_{\boldsymbol{idh}}^{'} \boldsymbol{\theta} + \delta_y + \tau_m + \varphi_h + \varepsilon_{ihd} \quad (4)$$

where all the variables share the same definition as the former equations. This regression includes all EV consumers, and non-EV consumers are not included. Fig. 7 plots the coefficients of β^hs after running regression (4). Figure panel (a) depicts β_1s—the impacts of EVs, panel (b) shows β_2s—the impacts of PVs, and panel (c) plots β_3s—the interaction between EV and PV adoption. The results are very similar to the former results in Fig. 5 except that there are slight increases during day hours (panel a). Panel (b) shows that net delivered electricity demand is negative during the day hours, meaning electricity generation after PVs occur mostly during the day, which is intuitive. Panel (c) indicates the co-adoption effects of EVs and PVs. The co-adoption results are consistent with former ones that with additional PV adoption, there is reduced

[6] It seems that the fluctuations happen every more than a year, which could be due to the way solar panels work and are maintained (e.g., dust cleaned off). It is possible that there are some engineering factors that also impact the efficiency of solar generation.

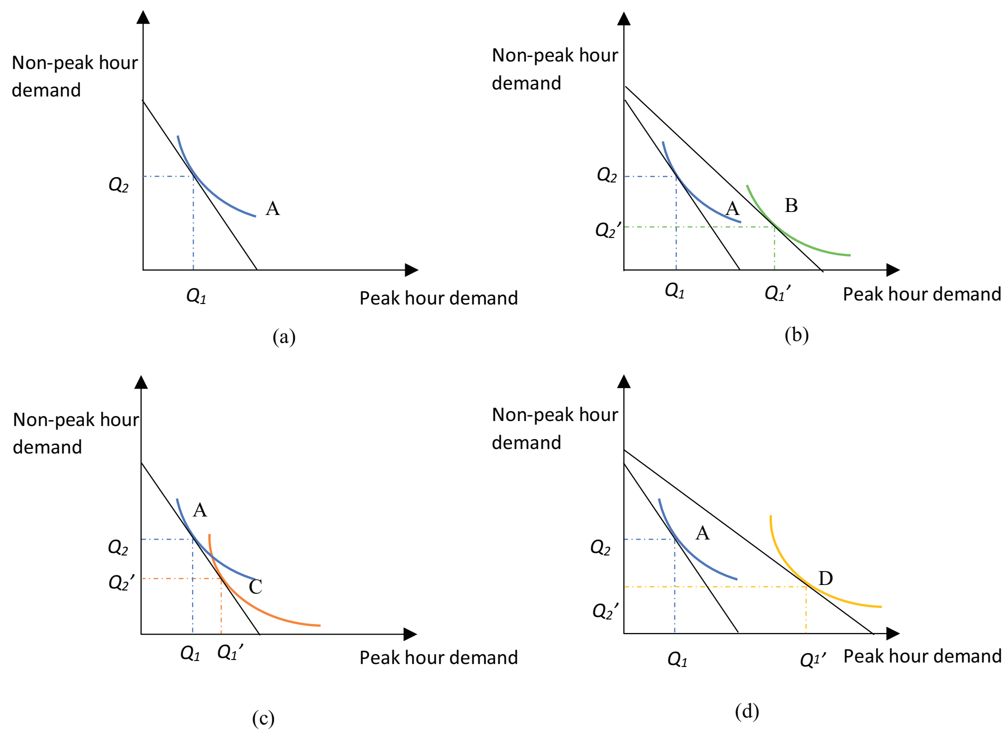

Fig. 1. Theoretical framework for EV consumers with additional PVs.
Notes: The curved lines refer to the indifference curves for consumers, and the downward sloping linear lines are the budget constraint lines. The steepness of the budget lines depends on the relative electricity prices of peak and non-peak hours. The cutpoint on the vertical axis is further away than that on the horizontal axis because the peak-hour price is higher than the non-peak hour price.

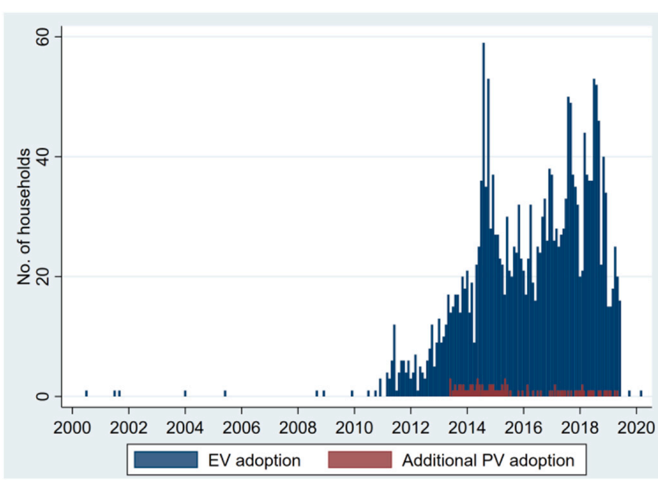

Fig. 2. Histogram of starting dates of EV in-home charging and PV adoption.

electricity demand for EV consumers during the night hours due to their environmental-driven behavioral changes where EV consumers prefer charging their EVs more with cleaner solar electricity and thus reduce their EV charging during the night (7 p.m.-7 a.m.). Overall, the results indicate that the co-adoption of PVs and EVs increases PV self-consumption during the hours when there is solar generation. This aligns with the literature (Denholm et al., 2013; Munkhammar et al., 2013; Hoarau and Perez, 2018), which shows that consumers' self-consumption of solar generation changes after introducing EVs. The details of the coefficients are displayed in Table A3.

In addition, because the EV and PV adoption is endogenous, we adopt a two-stage model for the adoption, as the best as we can, as one more robustness check. We predicted the adoption using a series of socio-demographic and housing characteristics obtained from the 2017 RET survey, including household income, square footage, household size, number of floors, vintage, age of household head, race, residence type (primary or seasonal residence), swimming pools, and dwelling type (single-family house, mobile house, or apartment). Then the predicted adoption is used in the second stage. The pattern seems consistent with the former analysis, which indicates a reduction in peak hour demand after adding PVs (Fig. A3). The reason why this approach is not used as the main approach is because of 1) the small number of consumers that have data on socio-demographics (<50); 2) the limited predictability of adoption (<0.3).

6. Private and social benefits of adding PVs for EV consumers

6.1. Private benefits

In this section, we estimate the private benefits of adding solar panels for an EV consumer. We calculate the daily private savings on bills by multiplying the estimated hourly electricity savings in kWh from Eq. (2) by their hourly electricity prices during a day. Then, we sum up all daily savings over a year and obtain the annual private savings.

The annual saved electricity is estimated to be 9866 kWh, which equals monetary savings of $930.6. The average payback period for additional solar panels, when combined with EVs, is estimated to be 10.3 years. During this payback period estimation, a discount rate of 5% is applied and the average solar panel costs are taken as $12,900 in Arizona.[7]

6.2. Environmental benefits

We estimate the environmental benefits resulting from less electricity demand by including four pollutants-CO_2, SO_2, NO_X, and PM2.5. We calculate the annual environmental benefits as a function of hourly marginal damages of electricity and the amount of electricity (Liang et al., 2020). The hourly marginal damages per kWh are obtained from (Holland et al., 2016), and we use the set of values that apply locally to

[7] Data about PV costs in Arizona is taken from Energysage. The 26% Federal Investment Tax Credit (ITC) is accounted for in the calculation.

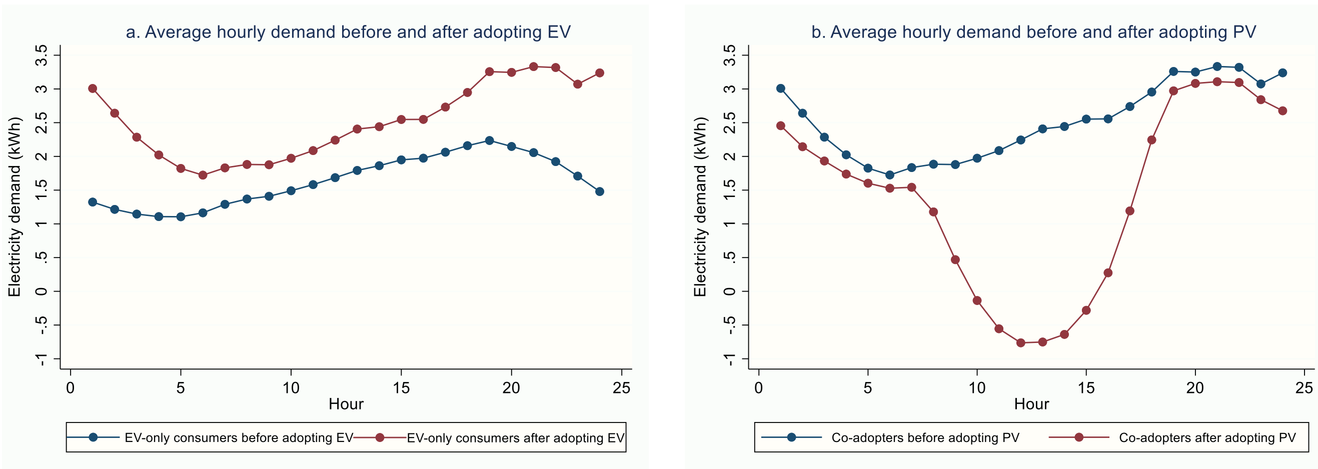

Fig. 3. Descriptive summary of net delivered hourly electricity demand after EV/PV adoption.
Notes: This figure plots the net delivered electricity from the utility to the households, rather than the total electricity demand including both net delivered electricity and the electricity generated from solar.

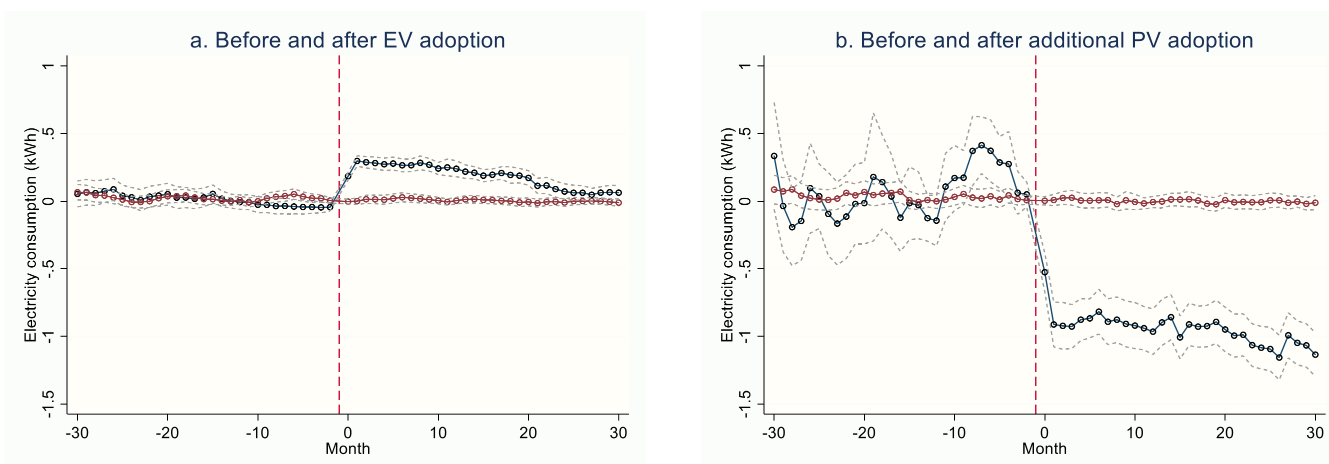

Fig. 4. The effect of EV and additional PV adoption on the average hourly electricity demand.
Notes: In panel (a), the treated group is EV-only consumers (blue line), and the control group is non-EV non-PV consumers (red line). In panel (b), the treated group is co-adoption consumers (blue line), and the control group is EV-only consumers (red line). Hypothetic treatment dates are assigned to the control groups. Both the coefficients and their 95% confidence intervals are plotted in the figures. The horizontal time axis is normalized relative to the month of the treatment and the excluded period is $t = -1$. We have dropped the observations before $t = -30$ and after $t = 30$. The regressions include Cooling Degree Days, Heating Degree Days, electricity prices, individual-consumer fixed effects, month-of-year, and year fixed effects. We also cluster the standard errors by the consumer level.
The larger noise or errors around electricity demand for solar adoption (panel b) is due to the smaller sample size and fewer households compared to EV adoption in panel (a). Standard errors decrease as the sample size increases, which gives a more accurate estimate (or smaller uncertainty) for the left panel.

Arizona (the Western Electricity Coordinating Council region). The marginal damages of electricity differ from hour to hour, depending on the fuel used on the margin for electricity generation. The amount of hourly electricity is taken from the same estimates based on Eq. (2). After multiplying the marginal damages by the electricity amount in a year, the annual environmental benefits are estimated to be $196.4. These environmental benefits are from the co-adoption of EVs and PVs, in addition to the emission benefits from driving EVs or adopting PVs.

We also estimate the average environmental benefits from driving EVs (other than gasoline vehicles) and adopting PVs. Suppose the environmental benefit is $0.03 per mile for driving EVs (Holland et al., 2016), and the annual average travel mileage is 7000 miles for EVs (Davis, 2019). This yields an annual environmental benefit of $210 from driving EVs. For adopting solar PV systems, their environmental benefits are calculated by multiplying the hourly emissions from electricity (Holland et al., 2016) by the hourly solar electricity generation. The hourly solar electricity generation is estimated using the PVWATTS model[8] for a typical 5 kW system (Table D1 in Liang et al., 2021). The annual environmental benefits of adopting a PV system are estimated to be $191. These calculations indicate that the co-adoption of EVs and PVs (or additional PVs for EVs) has a similar magnitude of environmental benefits as an EV or PV system, indicating that the co-adoption has greatly increased total environmental benefits.

6.3. Reduced social costs of electricity generation

The reduced social costs from electricity generation are long-term benefits, which are achieved through deferred infrastructure investments. They include three components: reduced generation fuel

[8] http://pvwatts.nrel.gov/pvwatts.php

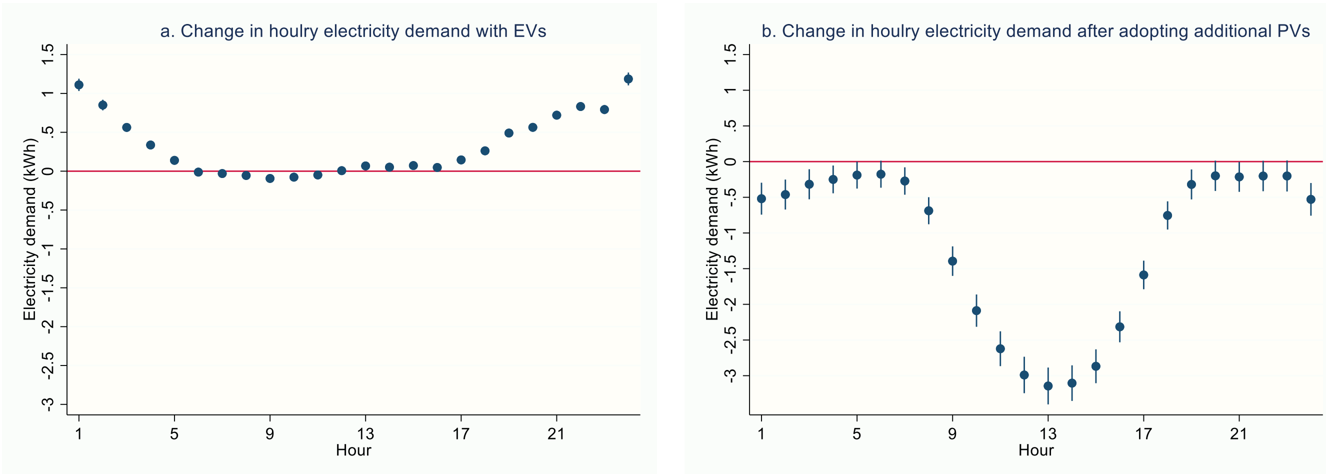

Fig. 5. Changes in hourly electricity demand after EV adoption and additional PV adoption.
Notes: The dependent variable is net hourly electricity demand (kWh). Panel (a) and panel (b) show the coefficients with 95% confidence intervals based on Eq. (1) and Eq. (2), respectively. Both regressions include consumer fixed effects and various time fixed effects (year, month, and hour fixed effects). Covariates of Cooling Degree Days, Heating Degree Days, hourly electricity prices, holiday dummy, and weekend dummy are also included in the regressions, and standard errors are clustered at the consumer level.

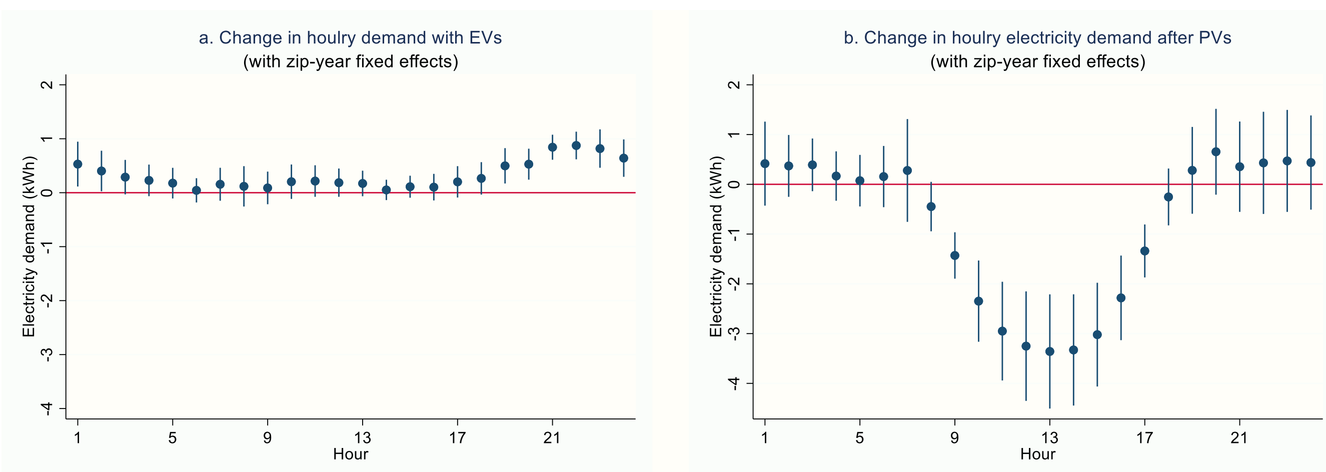

Fig. 6. Changes in hourly electricity demand including zip code-year fixed effects.
Notes: The dependent variable is net hourly electricity demand (kWh). Panel (a) shows the coefficients with 95% confidence intervals based on Eq. (1) and panel (b) plots the coefficients based on Eq. (2). Both regressions include consumer fixed effects and various time fixed effects (year, month, and hour fixed effects). Covariates such as Cooling Degree Days, Heating Degree Days, hourly electricity prices, holiday dummy, and weekend dummy are also included in the regressions, and standard errors are clustered at the consumer level.

costs, reduced capacity investments, and reduced transmission/distribution costs. The reduced fuel costs of generating electricity are estimated by making use of the hourly system lambdas from the Federal Energy Regulatory Commission.[9] The system lambdas are the minimal marginal fuel costs among all energy resources and they are used as the economic marginal costs of electricity generation in this paper. Then, the marginal fuel costs of electricity are multiplied by the total electricity savings to get the total saved generation fuel costs.

Next, we estimate the reduced capacity costs, which are determined by the largest amount of electricity that consumers demand (or utility needs to supply) during a month. To get the reduced capacity costs, we use the average monthly cost of capacity ($2.66/kW) multiplied by the largest average demand changes during a summer day (Novan and Smith, 2018; Liang et al., 2020). Lastly, we estimate the deferred transmission/distribution investments. The electricity transmission/distribution costs include expenses for building transmission infrastructure, purchasing transmission equipment, and installing transmission/distribution equipment. We multiply the average transmission/distribution costs (3.2 cents/kWh from http://eia.gov[10]) by the amount of electricity savings to get the total reduced transmission/distribution costs.

All the above estimated benefits and reduced costs are summarized in Table 1. The total social savings are the sum of environmental benefits, reduced fuel costs, reduced capacity investments, and reduced transmission/distribution costs. Table 1 shows that there are almost

[9] FERC 714 forms from https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data; https://www.e-education.psu.edu/eme801/node/532

[10] https://www.eia.gov/todayinenergy/detail.php?id=32812

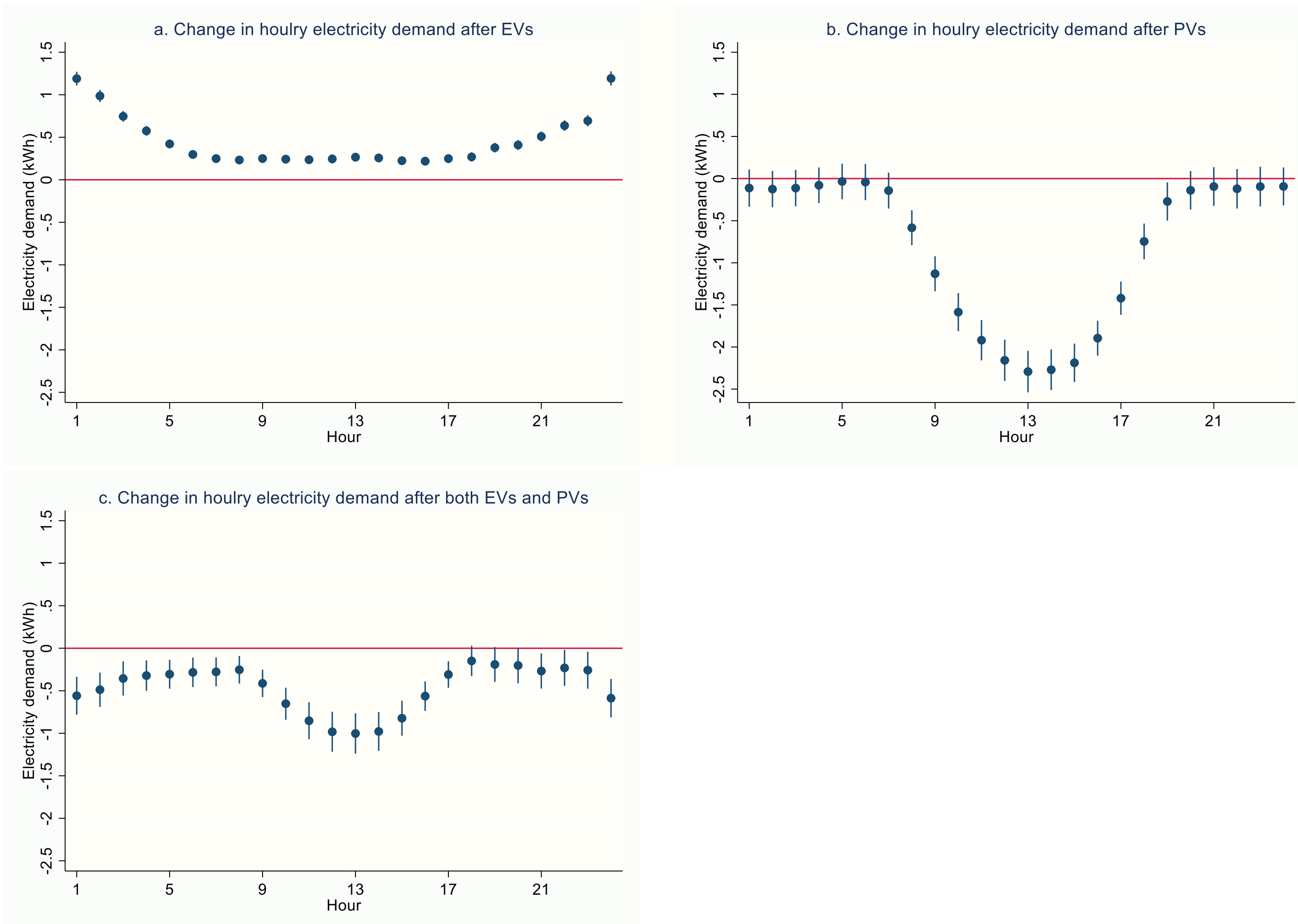

Fig. 7. Changes in hourly electricity demand after EV and PV adoption.
Notes: The dependent variable for all figures is net hourly electricity demand (kWh). The three sets of coefficients in panels (a), (b), and (c) are based on Eq. (4). All regressions include consumer fixed effects and various time fixed effects (year, month-of-year, and hour fixed effects). In the regression, covariables such as Cooling Degree Days, Heating Degree Days, hourly electricity prices, holiday dummy, and weekend dummy are also included, and standard errors are clustered at the consumer level.

Table 1
Summary of annual private and total social savings after adding solar for EV consumers.

	Estimated savings ($)	
	Mean	Confidence intervals
Total social savings	924.6	(751.1, 1094.5)
Environmental benefits	196.4	(154.1, 238.1)
Reduced fuel costs	312.1	(251.9, 371.1)
Reduced capacity investment	100.4	(92.1, 108.7)
Reduced transmission/distribution cost	315.7	(253.0, 376.6)
Total private savings	930.6	(755.2, 1101.4)

Notes: The confidence intervals are constructed based on bootstrapped standard errors. We draw from the distribution around our coefficients based on Eq. (2) 500 times using a bootstrap resampling method for panel data. During the bootstrapping, the observations are randomly selected by the panel (i.e., same consumer) rather than by individual observations.

equal private and social benefits after adding PVs for EV consumers although there are slightly higher private savings than the social savings.

7. Discussion and conclusion

This study provides insights into the near future, in which EVs and PVs are more closely interlinked. It explores the impact of additional PV adoption for EV consumers. The empirical findings are consistent with the conceptualization in the theoretical section and also indicate that Fig. 1 panel (d) in the theoretical framework is more likely to be the case in practice. Both income levels and preferences could affect consumers' electricity consumption behaviors. There are changes in income levels because the daily consumption decreases and there are private savings due to adding PVs. There are changes in preference because consumers now shift some of their EV charging to the hours during which solar panels generate electricity so that they are charging their EVs with cleaner electricity. This evidence of behavioral changes is in line with the findings of existing studies which show pro-environmental behavioral changes happen after the adoption of energy technologies. For example, load-shifting behaviors are observed for consumers after solar panel adoption (Keirstead, 2007; Stikvoort et al., 2020). Behavioral changes have also been reported for energy efficiency adoption in households (Azevedo, 2014; Gillingham et al., 2016) and after efficiency improvement for vehicles (Stapleton et al., 2016; Seebauer, 2018).

While it is unlikely that EV owners are always in the house, there are three potential ways that the behavioral changes observed in this study are more likely to happen. (1) EV owners could charge more during weekends. EV charging usually takes 4 h for level 2 chargers and around 20 h for level 1 chargers. Therefore, it is possible to fully charge EVs when individuals are at home during weekends. (2) Individuals drive other vehicles while leaving their EVs to be charged at home. It is shown that only 10% of U.S. households with EVs are single-vehicle households

(Davis, 2019) and most households have more than one vehicle. The EV owners in this study also reported that they have more than one car registered. It is possible that one EV is left at home to charge while people drive other vehicles. (3) Energy technology such as solar batteries helps people more easily to achieve behavioral changes. Thus, EV consumers could charge their EVs more with cleaner electricity and the pro-environmental behaviors are more likely to happen.

This study estimates the sample average treatment effects rather than the population average treatment effects. The SRP consumers are more representative of the consumers in hot and arid areas, which are interesting to examine because the consumers in hot areas are likely to increase due to climate change (Saunders et al., 2008) and they are also more vulnerable to climate change. Besides, our study on the SRP consumers can be reasonably generalized to all Phoenix consumers in Arizona. The SRP and Phoenix consumers are very similar in many characteristics (Table A4) although the SRP consumers are relatively healthier, more white, with newer houses, and also more likely to be homeowners, compared to average Phoenix consumers.

Our results also have implications for the design of new electricity price plans for the co-adopters. We show that additional PVs for EV consumers can reduce the peak loads while also decreasing total electricity demand. This implies that when more EV consumers pair the EV charging with PV systems, the need for investments in grid infrastructures will be decreased while electricity sales are also likely to reduce for the utilities. This adds to the concerns of the utilities about the loss of revenues and recouping of upfront costs. Appropriate residential rate structures should be proposed to ensure that these consumers are charged for their proper share of connecting to the grid (McLaren et al., 2015; Qiu et al., 2021).

The co-adoption of EVs and solar has both private and social benefits. The annual private savings for consumers are estimated to be ~$930 while there is also a similar magnitude of social benefits. Given the positive co-adoption effects, one policy implication for the policymakers is that incentives such as extra rebates for co-adopters should be provided to promote the co-adoption of EVs and solar panels. This co-adoption could facilitate the electrification of the residential sector and also greatly help with the mitigation of climate change.

Statement of data availability

The high-frequency electricity data are from the Salt River Project. As we are restricted by a non-disclosure agreement from SRP, the data are available upon reasonable request from researchers and also with permission from the SRP.

CRediT authorship contribution statement

Jing Liang: Conceptualization, Methodology, Formal analysis, Software, Writing – original draft, Visualization. **Yueming Qiu:** Conceptualization, Methodology, Funding acquisition, Writing – review & editing. **Bo Xing:** Data curation.

Acknowledgment

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Appendix

Table A1
Residential marginal electricity prices charged by the SRP utility.

Plan name	Season	On peak hours	Off peak hour	Super off-peak	Notes
E-21 Super peak Time-of-Use	Summer	$0.290	$0.083		On-peak hours are 3–6 p.m. Monday to Friday and the rest are off-peak hours.
	Summer peak	$0.344	$0.085		
	Winte r	$0.106	$0.074		
E-22 Super peak Time-of-Use	Summer	$0.290	$0.083		On-peak hours are 4–7 p.m. Monday to Friday and the rest are off-peak hours.
	Summer peak	$0.344	$0.085		
	Winter	$0.106	$0.074		
		0–2000 kWh	2001+ kWh		
E-23 Standard price plan	Summer	$0.109	$0.113		
	Summer peak	$0.116	$0.127		
	Winter	$0.078			
E-25 Super peak Time-of-Use	Summer	$0.290	$0.083		On-peak hours are 2–5 p.m. Monday to Friday and the rest are off-peak hours.
	Summer peak	$0.344	$0.085		
	Winter	$0.106	$0.074		
E-26 Standard Time-of-Use	Summer	$0.209	$0.073		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	$0.241	$0.073		
	Winter	$0.095	$0.069		
E-27 Customer generation plan	Summer	$0.046	$0.036		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	$0.062	$0.041		
	Winter	$0.041	$0.037		
E-29 Electric vehicle price plan	Summer	$0.209	$0.077	$0.061	On-peak hours are 2–8 p.m. in summer and 5–9 a.m. & 5–9 p.m. in winter, Monday to Friday. Super off-peak hours are 11 p.m.-5 a.m. The rest are off-peak hours.
	Summer peak	$0.241	$0.077	$0.061	
	Winter	$0.095	$0.074	$0.058	

Notes: Summer season for billing purpose, includes May, June, September and October. Summer peak inlcudes July and August. Winter season is from November to April.

Table A2
Impacts on electricity demand by hour-of-day for EV adoption and additional PV adoption.

Variables	Non-EV non-PV consumers vs. EV-only consumers	Variables	EV-only consumers vs. co-adopters of EVs and PVs
Hour1 *EV_only	1.110***	Hour1*EV*Solar	−0.519***
	(0.040)		(0.114)
Hour2 *EV_only	0.851***	Hour2*EV*Solar	−0.462***
	(0.035)		(0.107)
Hour3 *EV_only	0.563***	Hour3*EV*Solar	−0.317***
	(0.029)		(0.107)
Hour4 *EV_only	0.337***	Hour4*EV*Solar	−0.249**
	(0.026)		(0.099)
Hour5 *EV_only	0.139***	Hour5*EV*Solar	−0.189*
	(0.022)		(0.096)
Hour6 *EV_only	−0.012	Hour6*EV*Solar	−0.177*
	(0.021)		(0.096)
Hour7 *EV_only	−0.030	Hour7*EV*Solar	−0.272***
	(0.021)		(0.098)
Hour8 *EV_only	−0.055***	Hour8*EV*Solar	−0.688***
	(0.021)		(0.097)
Hour9 *EV_only	−0.093***	Hour9*EV*Solar	−1.394***
	(0.021)		(0.105)
Hour10 *EV_only	−0.077***	Hour10*EV*Solar	−2.088***
	(0.021)		(0.115)
Hour11 *EV_only	−0.049**	Hour11*EV*Solar	−2.622***
	(0.021)		(0.124)
Hour12 *EV_only	0.007	Hour12*EV*Solar	−2.990***
	(0.021)		(0.130)
Hour13 *EV_only	0.068***	Hour13*EV*Solar	−3.144***
	(0.021)		(0.132)
Hour14 *EV_only	0.051**	Hour14*EV*Solar	−3.104***
	(0.021)		(0.127)
Hour15 *EV_only	0.072***	Hour15*EV*Solar	−2.868***
	(0.021)		(0.121)
Hour16 *EV_only	0.048**	Hour16*EV*Solar	−2.315***
	(0.022)		(0.111)
Hour17 *EV_only	0.145***	Hour17*EV*Solar	−1.588***
	(0.023)		(0.102)
Hour18 *EV_only	0.262***	Hour18*EV*Solar	−0.754***
	(0.024)		(0.101)
Hour19 *EV_only	0.490***	Hour19*EV*Solar	−0.320***
	(0.026)		(0.107)
Hour20 *EV_only	0.564***	Hour20*EV*Solar	−0.199*
	(0.026)		(0.108)
Hour21 *EV_only	0.720***	Hour21*EV*Solar	−0.214**
	(0.026)		(0.107)
Hour22*EV_only	0.832***	Hour22*EV*Solar	−0.202*
	(0.028)		(0.109)
Hour23 *EV_only	0.793***	Hour23*EV*Solar	−0.201*
	(0.030)		(0.111)
Hour24 *EV_only	1.186***	Hour24*EV*Solar	−0.529***
	(0.042)		(0.117)
CDD	0.054***		0.065***
	(0.000)		(0.001)
HDD	0.035***		0.035***
	(0.000)		(0.001)
Electricity price	−1.269***		−3.961***
	(0.059)		(0.181)
Weekend	0.092***		0.019***
	(0.002)		(0.005)
Holiday	0.040***		−0.073***
	(0.002)		(0.005)
_cons	1.495***		3.689***
	(0.017)		(0.070)
No. of obs.	171 M		46 M
R^2	0.281		0.269

Notes: The results are from the regression models (1) and (2). Individual fixed effects, as well as year, month-of-year, and hour-of-day fixed effects are included. Standard errors are in the parentheses with *,**, and *** showing $p < 0.10$, $p < 0.05$ and $p < 0.01$. Standard errors are clustered at the individual consumer level.

Table A3
Impacts on electricity demand by hour-of-day for EV adoption and additional PV adoption using a secondary DID analysis.

Variables	Coefficients	Variables	Coefficients	Variables	Coefficients
Hour1 *EV_only	1.190***	Hour1 *Solar	−0.113	Hour1*EV*Solar	−0.558***
	(0.041)		(0.113)		(0.114)
Hour2 *EV_only	0.986***	Hour2 *Solar	−0.125	Hour2*EV*Solar	−0.488***

(*continued on next page*)

Table A3 (*continued*)

Variables	Coefficients	Variables	Coefficients	Variables	Coefficients
	(0.037)		(0.110)		(0.103)
Hour3 *EV_only	0.746***	Hour3 *Solar	−0.113	Hour3*EV*Solar	−0.355***
	(0.032)		(0.110)		(0.103)
Hour4 *EV_only	0.575***	Hour4 *Solar	−0.080	Hour4*EV*Solar	−0.321***
	(0.029)		(0.108)		(0.091)
Hour5 *EV_only	0.421***	Hour5 *Solar	−0.035	Hour5*EV*Solar	−0.305***
	(0.026)		(0.108)		(0.086)
Hour6 *EV_only	0.298***	Hour6 *Solar	−0.042	Hour6*EV*Solar	−0.284***
	(0.025)		(0.110)		(0.088)
Hour7 *EV_only	0.249***	Hour7 *Solar	−0.143	Hour7*EV*Solar	−0.278***
	(0.025)		(0.109)		(0.087)
Hour8 *EV_only	0.233***	Hour8 *Solar	−0.584***	Hour8*EV*Solar	−0.253***
	(0.026)		(0.106)		(0.083)
Hour9 *EV_only	0.250***	Hour9 *Solar	−1.130***	Hour9*EV*Solar	−0.413***
	(0.026)		(0.106)		(0.082)
Hour10 *EV_only	0.242***	Hour10 *Solar	−1.586***	Hour10*EV*Solar	−0.652***
	(0.027)		(0.115)		(0.096)
Hour11 *EV_only	0.236***	Hour11 *Solar	−1.919***	Hour11*EV*Solar	−0.853***
	(0.027)		(0.122)		(0.111)
Hour12 *EV_only	0.245***	Hour12 *Solar	−2.158***	Hour12*EV*Solar	−0.982***
	(0.027)		(0.125)		(0.120)
Hour13 *EV_only	0.266***	Hour13 *Solar	−2.292***	Hour13*EV*Solar	−1.002***
	(0.026)		(0.126)		(0.121)
Hour14 *EV_only	0.257***	Hour14 *Solar	−2.270***	Hour14*EV*Solar	−0.979***
	(0.026)		(0.123)		(0.116)
Hour15 *EV_only	0.225***	Hour15 *Solar	−2.188***	Hour15*EV*Solar	−0.823***
	(0.026)		(0.116)		(0.105)
Hour16 *EV_only	0.219***	Hour16 *Solar	−1.895***	Hour16*EV*Solar	−0.563***
	(0.026)		(0.105)		(0.088)
Hour17 *EV_only	0.249***	Hour17 *Solar	−1.420***	Hour17*EV*Solar	−0.309***
	(0.027)		(0.100)		(0.080)
Hour18 *EV_only	0.269***	Hour18 *Solar	−0.746***	Hour18*EV*Solar	−0.149
	(0.028)		(0.108)		(0.091)
Hour19 *EV_only	0.378***	Hour19 *Solar	−0.272**	Hour19*EV*Solar	−0.190*
	(0.029)		(0.115)		(0.105)
Hour20 *EV_only	0.409***	Hour20 *Solar	−0.139	Hour20*EV*Solar	−0.202*
	(0.030)		(0.117)		(0.107)
Hour21 *EV_only	0.509***	Hour21 *Solar	−0.095	Hour21*EV*Solar	−0.268**
	(0.030)		(0.117)		(0.105)
Hour22*EV_only	0.637***	Hour22 *Solar	−0.121	Hour22*EV*Solar	−0.231**
	(0.032)		(0.120)		(0.108)
Hour23 *EV_only	0.694***	Hour23 *Solar	−0.095	Hour23*EV*Solar	−0.258**
	(0.034)		(0.120)		(0.111)
Hour24 *EV_only	1.192***	Hour24 *Solar	−0.093	Hour24*EV*Solar	−0.587***
	(0.043)		(0.115)		(0.115)
CDD					0.066***
					(0.001)
HDD					0.035***
					(0.001)
Electricity price					−3.340***
					(0.151)
Weekend					0.055***
					(0.004)
Holiday					−0.027***
					(0.004)
_cons					2.473***
					(0.040)
No. of obs.					73 M
R^2					0.292

Notes: The results are all from the regression model based on Eq. (4). Individual fixed effects, as well as year, month-of-year, and hour-of-day fixed effects are included. Standard errors are in the parentheses with *,**, and *** showing $p < 0.10$, $p < 0.05$ and $p < 0.01$. Standard errors are clustered at the individual consumer level.

Table A4
Comparison of sociodemographic and building attributes for Phoenix and SRP consumers.

	Phoenix, Arizona (Census)	SRP sample in this study[g]
Median Household income	$60.9k[a]	62.5 k
Average monthly electricity consumption	1114 kWh[b]	1245 kwh
Square footage	1832[c]	1770
White	68.2%[a]	70.0%
Household size	2.82[a]	2.59
Vintage	36 years[d]	26 years
Ownership	55.6%[a]	73.0%
Single family house percentage	69%[e]	61%
Age of householder	51.8 years[f]	52.6 years

[a] https://www.census.gov/quickfacts/fact/table/phoenixcityarizona,US.
[b] Arizona mean: https://www.eia.gov/electricity/data.php#sales;
[c] https://ktar.com/story/2246976/when-it-comes-to-house-size-phoenix-is-kind-of-a-big-deal/
[d] https://www.bestplaces.net/housing/city/arizona/phoenix
[e] https://censusreporter.org/profiles/31000US38060-phoenix-mesa-chandler-az-metro-area/
[f] https://www.bls.gov/regions/west/news-release/consumerexpenditures_phoenix.htm
[g] SRP consumers' characteristics are obtained from the Residential Equipment and Technology (RET) surveys conducted in 2017 by the Salt River Project utility.

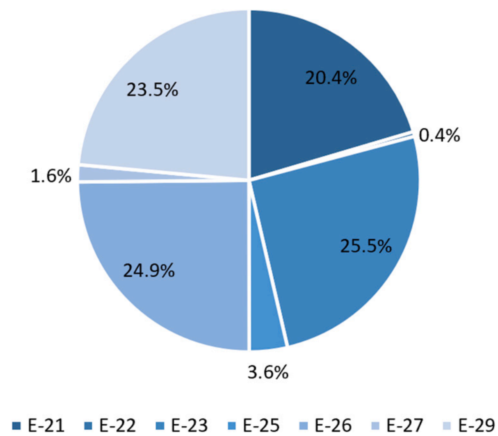

Fig. A1. Distribution of consumers on different price plans.

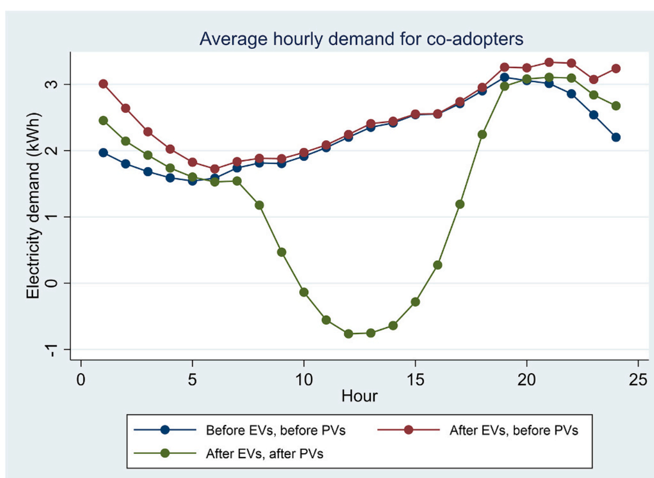

Fig. A2. Net delivered hourly electricity demand after EV/PV adoption for co-adopters.

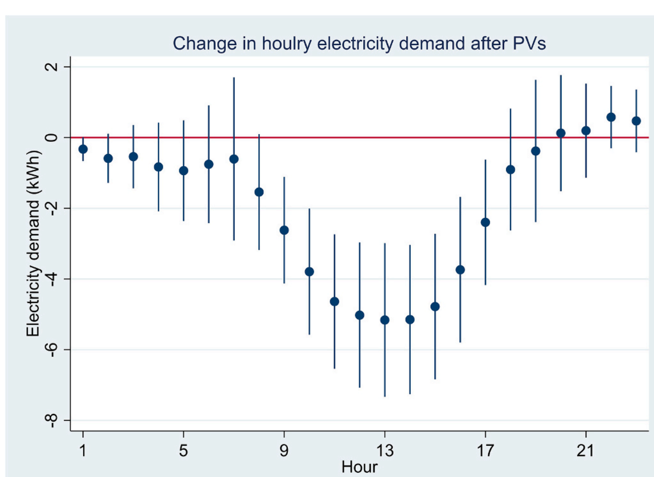

Fig. A3. Changes in hourly electricity demand after additional PV adoption.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106170.

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