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Quantifying the rebound effects of residential solar panel adoption☆

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A B S T R A C T

Customers who adopt solar panels can reduce their energy bills and lower the effective average electricity prices they pay. When the price falls, a solar consumer might consume more electricity than before – a solar rebound effect. We provide the first empirical evidence of residential solar rebound effects in the U.S. We use household level hourly and daily electricity meter data as well as hourly solar panel electricity generation data from 277 solar homes and about 4000 non-solar homes from 2013 to 2017 in Phoenix Arizona. Using matching methods and a fixed effects panel regression approach, we find that when solar electricity generation increases by 1 kWh, solar homes increase their total electricity consumption by 0.18 kWh. This indicates that solar rebound effects are estimated at 18%. Building upon our theoretical framework, the increase in consumer surplus from solar panel adoption is estimated at $972/yr.

1. Introduction

Distributed solar energy technologies such as rooftop and ground-mounted solar photovoltaics (PV) are widely regarded as key options for reducing society's reliance on fossil-fuel-generated electricity, the associated carbon emissions, and other environmental challenges (Marszal et al., 2011; Parida et al., 2011). There have been many policy discussions centered around distributed solar PV. On the benefit side, policy evaluations involve increased consumer surplus from saved energy bills and a positive impact on the environment (Chan and Gillingham, 2015). There are also debates about potentially negative impacts. Electric utilities need to collect sufficient revenue to recoup the upfront cost of capital investment in infrastructure. The transmission and distribution system is sized to meet customer maximum demand. The continuously increasing penetration of distributed solar energy technologies has raised significant challenges for the utilities to recoup their upfront cost from kilowatt-hour (kWh) sales due to an electricity sales reduction (McLaren et al., 2015; Hledik, 2014). Electric utilities need to

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raise their electricity tariffs to deal with such issues (Johnson et al., 2017). This then leads to an ongoing discussion on the distributional impact between solar consumers who are generally associated with higher socio-income status and non-solar customers who are generally not (Liang et al., 2018a).

A central part of the policy discussion is that solar customers reduce their energy bills from the electric utilities. Naturally, one can use the amount of electricity generated by solar panels to calculate the amount of reduction in electricity purchase from the utilities. This is what has been done in existing integrated assessment and simulation models such as Global Change Assessment Model (GCAM). If electricity consumers always consume the same amount of power, then any increase in power generation by solar panels reduces the need for conventional power generation. This one for one displacement effect is unlikely to unfold because solar adoption effectively reduces consumers' energy bills and thus the average price that consumers pay for electricity. When the average electricity price falls, solar consumers might consume more electricity than before. In the language of energy economics, this triggers a rebound effect.

Rebound effects are widely discussed in energy efficiency literature (e.g., Liang et al., 2018b; Gillingham et al., 2016; Azevedo, 2014; Qiu, 2014; Thomas and Azevedo, 2013). However residential solar literature has not quantified such rebound effects except for one Australian study (Deng and Newton, 2017). Our unique contributions compared to Deng and Newton (2017) are four folds. First, we are the first to examine the rebound effects of net-metered solar consumers while Deng and Newton only look at gross-metered solar homes. These two types of solar customers might have different causal mechanisms for solar rebound effects. For gross-metered solar homes, solar customers export all their solar electricity in return for feed-in credits, while for net-metered customers, solar electricity is first being consumed by the customer and if there is any solar electricity left it can be sold back to the grid. As a result, the main cause of rebound for gross-metered solar customers is the perceived increase in "income" from selling all solar electricity while the main cause of rebound for net-metered solar customers is the reduced perceived average price from consuming "free" solar electricity. In the U.S. more than 40 states have net-metering policies, so our results have very important and broad policy implications. Second, the higher frequency data in our study enables us to use more flexible fixed effects to control for more confounding factors, such as using customer-year fixed effects to control for time-variant unobservables for individual consumer while it is impossible to use such fixed effects for quarterly data in Deng and Newton. Third, the hourly level analysis in our paper enables us to evaluate more precisely the environmental benefit of solar panels using actual change in hourly electricity needed from the grid, because the marginal damage factors from environmental pollutants associated with electricity supply differ by hour of day. Last but not the least, we provide the first empirical evidence of solar rebound effects in the U.S. while Deng and Newton look at Australian consumers.

To the best of our knowledge, our paper is the first that uses high frequency residential meter data as well as solar meter data at the household level of a large sample of representative households to provide precise estimation of rebound effects for net-metered solar homes in the U.S. We answer two research questions. First, how large is the rebound effect of residential solar customers? Second, after considering rebound effects, what are the increased consumer surplus and the value of reduction in environmental pollutants and greenhouse gas emissions from solar panel adoption?

We first build a consumer-theoretical framework to show the relationships among price elasticity of electricity demand, solar electricity generation, response to solar generation, and change in consumer surplus. Then we use household level hourly and daily electricity meter data as well as hourly solar panel electricity generation data from 277 solar homes and about 4000 non-solar homes from 2013 to 2017 in the Phoenix metropolitan area of Arizona to provide empirical evidence. We rely on matching method and fixed effects panel regression to control for potential endogeneity issues. Results show that on average, when solar electricity generation increases by 1 kWh, solar homes increase their total electricity consumption by 0.18 kWh, implying that solar rebound effects are 18%. We show theoretically that this response to solar electricity generation should be equal to price elasticity of electricity consumption. We also find that consumers located in more liberal neighborhoods experience lower rebound effects, suggesting that environmental awareness plays a role. The main policy implication of our paper is that when evaluating the impacts of solar panel adoption and designing the appropriate rate structure, policy makers and utilities should consider the extra amount of electricity consumed by solar customers due to rebound effects. We discuss in more details our contributions to existing literature in Section 7.

2. Theoretical framework

First, we need to define explicitly what types of rebound effects we are examining. We are examining only microeconomic rebound effects and not considering macroeconomic rebound effects which include overall market adjustments and innovation channels. There are two types of microeconomic rebound effects: the direct rebound and the indirect rebound. The direct rebound is focused on change in energy use due to change in the usage of a specific service or product (e.g., an air conditioner or a refrigerator). In existing economics literature, fuel price elasticities of demand are commonly estimated to calculate direct rebound effects. The indirect rebound considers the change in energy use because of change in the usage of other energy technologies (e.g., how much electricity is consumed for air conditioning after the household installs a more energy-efficient washing machine), due to substitution and income effects. In our paper, the estimated rebound effects include both direct and indirect rebound effects because we are focusing on electricity consumption at the household level instead of at a specific service level.

We now provide a theoretical framework to conceptualize the rebound effects of residential solar customers. We denote a household's daily electricity consumption prior to adopting solar panels as e_0. Following Ito (2014), we assume that residential electric consumers respond to average electricity price instead of marginal electricity price. We denote the average electricity price as p_0. After installing solar panels, electricity generated by solar panels is e_s. To consumers solar electricity is valued at the retail rate or at the same average electricity price. The new electricity bill is equal to $p_0(e_0 - e_s)$. Then the effective average energy price becomes $p_s = p_0(e_0 - e_s)/e_0 = (1 - e_s/e_0)p_0 < p_0$. The larger the amount of solar electricity generation, the lower the post-adoption effective electricity price compared to the original average electricity price. If consumers' price elasticity of electricity consumption is ξ, by definition $\xi = \frac{\Delta e/e}{\Delta p/p} = \frac{\partial e}{\partial p}\frac{p}{e}$. Then $\xi = \frac{\Delta e/e_0}{(p_s - p_0)/p_0} = \frac{\Delta e/e_0}{\left(\left(1-\frac{e_s}{e_0}\right)p_0 - p_0\right)\Big/ p_0} = \frac{\Delta e/e_0}{-\frac{e_s}{e_0}}$, which implies that $-\frac{e_s}{e_0}\xi e_0 = \Delta e$. Then the new consumption level after adopting solar panels is expected to be

$$e_{post} = \Delta e + e_0 = -\frac{e_s}{e_0}\xi e_0 + e_0 = e_0\left(1 - \frac{e_s}{e_0}\xi\right) = e_0 - \xi e_s \tag{1}$$

From equation (1), we know that since consumers have negative price elasticity of demand for electricity, $e_{post} > e_0$. Also, the larger the amount of electricity generated by solar panels (e_s), the higher e_{post} will be. To examine the relationship between e_{post} and e_s, we have

$$\frac{\partial e_{post}}{\partial e_s} = -\xi \tag{2}$$

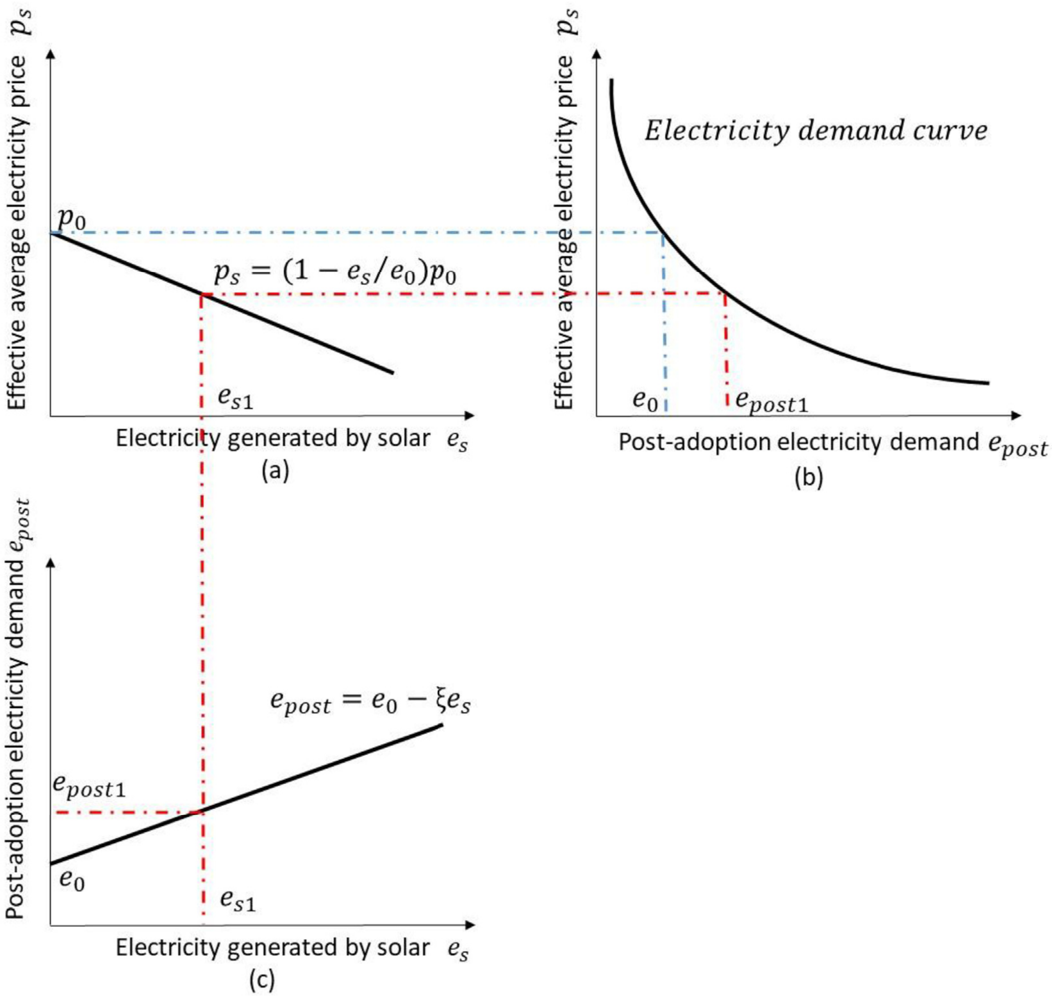


Fig. 1. Illustration of the relationship among solar electricity generation, price elasticity of consumption, and rebound effects.

The rebound effect is then equal to ξ, which measures the percentage of energy savings that is "taken back" by behavioral change. Fig. 1 illustrates the relationship among solar electricity generation, price elasticity of consumption, and rebound effects.

3. Data and descriptive statistics

We study the residential solar sector in the Phoenix metropolitan area of Arizona. Arizona is a great case study for solar policy research because it is abundant in solar resources and there is great potential for diffusion of distributed solar energy (Qiu et al., 2017). As of mid 2018, the installed solar panels rank 3rd in U.S. (SEIA, 2018). We obtain the main data for our analysis from Salt River Project (SRP), a major utility company whose service territory covers several cities in the Phoenix metropolitan area. There are two phases of SRP's residential solar policy based on whether the solar panel permits were applied for before or after December 2014. For permits before December 2014, solar customers could be on any type of residential rate plans. For these rate plans, the portion of electricity generated by solar panels that is directly consumed by customers is valued at the retail rate. The excess electricity sold back to the grid is also valued at the retail rate except for the billing cycle of April. For April billing cycle, the excess electricity is purchased back by SRP at wholesale electricity price. In December 2014, SRP started a new solar customer net metering plan for all solar panels whose permits were applied for after December 2014. The new rate plan imposes a demand charge for solar customers but also lowers the marginal electricity prices. In our dataset, there is only one solar consumer who applied for the permit after December 2014. We dropped this solar customer to avoid any potential confounding factors because of the pricing change.

In order for consumers to perceive a lower average electricity price when there is solar electricity, they need to know the information of their total bills and the total electricity consumption, instead of just knowing the grid-based consumption amount. Figure A1 is an example of the monthly bills for a typical solar consumer of SRP. The portion of the bills highlighted in the orange box shows the total electricity consumption information, including both the grid-based consumption and consumption of solar electricity. As a result, solar consumers can indeed perceive a lower average price than non-solar consumers through dividing their bills by total consumption.

We obtained several separate datasets from SRP. The first dataset is a Residential Equipment and Technology (RET) survey conducted by SRP in early 2014. The survey asked about detailed socio-demographics, building characteristics, appliance and other energy technology attributes, and energy consumption behaviors. About 16,000 completed responses were received. The second dataset is detailed information of solar customers that also completed the 2014 RET survey. This includes hourly electricity generated by each solar household from 2013 to 2017, installation date, cost per kW, system size, and financing mode (lease or own) for each household. The third dataset contains high frequency (every 15 min) electricity meter data from 2013 to 2017 for each customer that completed the RET survey. Lastly, we obtained daily register read meter data for each customer. We now describe in more details the relationships among different types of meter data.

For any given hour h, we denote the amount of electricity delivered from the grid to the customer as kWh_{ch}, the amount of electricity received by the grid from the customer as kWh_{gh}, and the amount of electricity generated by the solar panel of the customer as kWh_{sh} . At any given hour, if solar panels generate electricity, the solar electricity will be first consumed by the customer before sending the remainder back to the grid. If the customer consumes more than the generated solar electricity, then the grid will deliver kWh_{ch} to the customer. If the customer consumes less than the generated solar electricity, then the grid will receive kWh_{gh} from the customer. For the register read data, for a given day d, we denote the register read data at the end of day d as $READ_d$. Then the net electricity purchased from the grid for day d is $\mathrm{kWh}_d = READ_d - READ_{d-1}$. We should have $\mathrm{kWh}_d = \sum_{h=1}^{24}(\mathrm{kWh}_{ch} - \mathrm{kWh}_{gh})$. We can also obtain the gross electricity consumption (electricity consumed from both solar panels and the grid) of the customer on day d by summing up the net electricity purchase and solar electricity as follows $\mathrm{Cons}_d = \sum_{h=1}^{24}(\mathrm{kWh}_{ch} + \mathrm{kWh}_{sh} - \mathrm{kWh}_{gh}) = \mathrm{kWh}_d + \sum_{h=1}^{24}\mathrm{kWh}_{sh} = \mathrm{kWh}_d + \mathrm{kWh}_{sd}$. For high frequency meter data, we only have the information on kWh_{ch} but not on kWh_{gh}. As a result, we analyze gross electricity consumption at daily level while we analyze electricity delivered to the customer at hourly level.

Table 1 (a-c) list the summary statistics for key variables. For installed solar-panel system attributes, the average system size is 6.6 kW (in AC), and average cost per kW capacity is $5176/kW. Table 1(b) lists the electricity usage attributes. Figure A2 lists distribution of solar panel characteristics over the years in our sample. Most solar panels in our analysis were installed in 2013–2015.[1] Fig. 2 shows the distribution of daily electricity generation from solar panels and there is a wide distribution of the amount of electricity generated per panel system and also per kW. Fig. 3 shows average hourly electricity delivered for customers for solar and for non-solar customers. Solar customers dropped their electricity delivered from the grid during solar generation hours. Table 1(c) compares the household and building attributes between solar and non-solar customers, prior to matching. Solar and non-solar customers differ in certain attributes. More solar customers are owner-occupied and

[1] Note that even though we dropped the solar customers that are on the new net-metering plan after the policy change in 2014, there are still customers installing solar panels after 2014 but are not on the new net-metering plan. This is because they applied for the permit prior to the policy change, but it took them some time to install the panels.

Table 1
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Table 1a. Solar panel attributes					
System size (KW AC)	277	6.61	2.76	0.7	21.50
Cost (1000$/kW)	265	5.18	1.67	2.2	13.30
Installation year	277	2012.57	2.16	2006	2016
All year_daily solar electricity generation per system (kWh)	459,844	30.33	18.45	0	166.56
Summer_daily solar electricity generation per system (kWh)	220,951	34.04	18.80	0	163.2
Winter_daily solar electricity generation per system (kWh)	238,893	26.90	17.43	0	166.56
All year_daily solar electricity generation per kW(kWh/kW)	458,456	4.76	1.86	0	15.38

Variable	Obs	Mean	Std. Dev.	Min	Max
Table 1b. Electricity usage attributes					
No Solar					
Average daily electricity price ($/kWh)	5,200,885	0.10	0.02	0.0701	0.13
All year_daily electricity consumption (kWh/day)	5,200,885	37.85	28.66	0	585.72
Summer_daily electricity consumption (kWh/day)	2,673,750	47.92	32.13	0	585.72
Winter_daily electricity consumption (kWh/day)	2,527,135	27.18	19.43	0	385.10
All year_net electricity purchase from the grid (kWh/day)	5,200,885	37.85	28.66	0	585.72
Summer_net electricity purchase from the grid (kWh/day)	2,673,750	47.92	32.13	0	585.72
Winter_net electricity purchase from the grid (kWh/day)	2,527,135	27.18	19.43	0	385.10
All year_hourly electricity delivered to the customer (kWh/hour)	80,214,189	1.59	1.58	0	98.92
Summer_hourly electricity delivered to the customer (kWh/hour)	41,304,228	2.02	1.78	0	46.34
Winter_hourly electricity delivered to the customer (kWh/hour)	38,909,961	1.14	1.19	0	98.92
With solar					
Average daily electricity price ($/kWh)	213,864	0.09	0.02	0.0701	0.13
All year_daily electricity consumption (kWh/day)	213,864	46.63	30.64	0	289.09
Summer_daily electricity consumption (kWh/day)	102,947	60.09	34.19	0	289.09
Winter_daily electricity consumption (kWh/day)	110,917	34.14	20.01	0	237.99
All year_net electricity purchase from the grid (kWh/day)	213,864	18.45	27.75	0	261.00
Summer_net electricity purchase from the grid (kWh/day)	102,947	28.86	30.37	0	261.00
Winter_net electricity purchase from the grid (kWh/day)	110,917	8.79	20.86	0	209.00
All year_hourly electricity delivered to the customer (kWh/hour)	7,204,364	1.29	1.50	0	24.83
Summer_hourly electricity delivered to the customer (kWh/hour)	3,538,491	1.63	1.71	0	22.29
Winter_hourly electricity delivered to the customer (kWh/hour)	3,665,873	0.96	1.18	0	24.83

Variable	Obs	Mean	Std. Dev.	Min	Max
Table 1c. Household and building attributes					
No Solar					
Owner occupied	4058	0.73	0.45	0	1
TOU pricing	4058	0.36	0.48	0	1
Household income	4058	52.68	42.51	3.75	150
Square footage	3898	1.62	0.82	0.75	3
Number of persons in the household	3899	2.19	1.13	1.5	5
Household head being white	3824	0.75	0.43	0	1
Number of stories	3817	1.21	0.45	1	3
Vintage of the house in years	4058	29.38	18.16	7.5	65
Age of household head	3804	57.15	15.93	25	75
Primary residence	3943	0.93	0.26	0	1
Having a swimming pool	4032	0.25	0.43	0	1
Single family house	3872	0.77	0.42	0	1
Having programmable thermostats	4058	0.58	0.49	0	1
Solar customers					
Owner occupied	277	0.92	0.28	0	1
TOU pricing	277	0.48	0.50	0	1
Household income	277	68.66	44.73	3.75	150
Square footage	275	2.06	0.72	0.75	3
Number of persons in the household	272	2.44	1.24	1.5	5
Household head being white	260	0.76	0.43	0	1
Number of stories	270	1.20	0.42	1	3
Vintage of the house in years	277	29.61	18.30	7.5	50
Age of household head	270	56.85	14.26	25	75
Primary residence	273	0.95	0.23	0	1
Having a swimming pool	277	0.41	0.49	0	1
Single family house	271	0.99	0.12	0	1
Having programmable thermostats	277	0.74	0.44	0	1

on Time-of-use (TOU) pricing than non-solar customers. Solar customers have higher household income, larger square footage, more people in the household, as well as a higher likelihood to have a swimming pool, programmable thermostats,

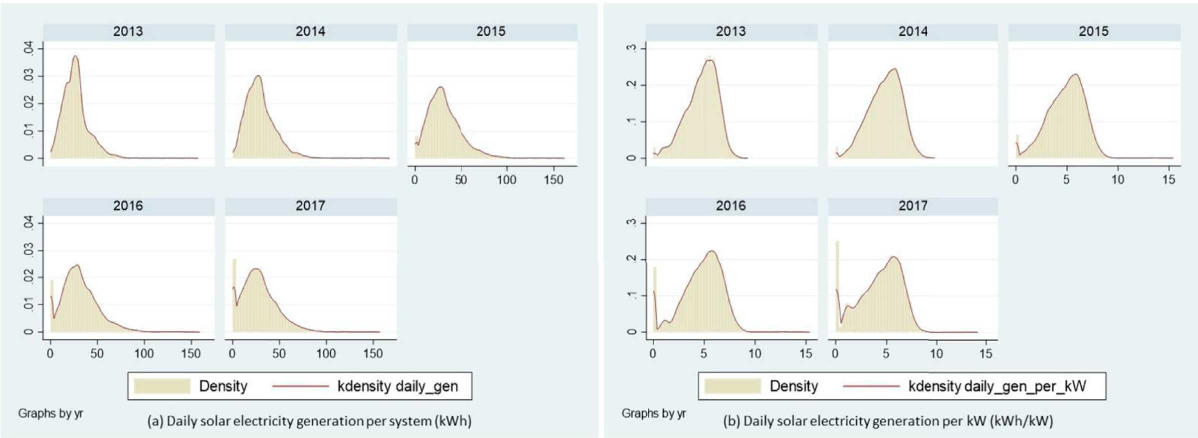


Fig. 2. Daily electricity generated by solar panels.

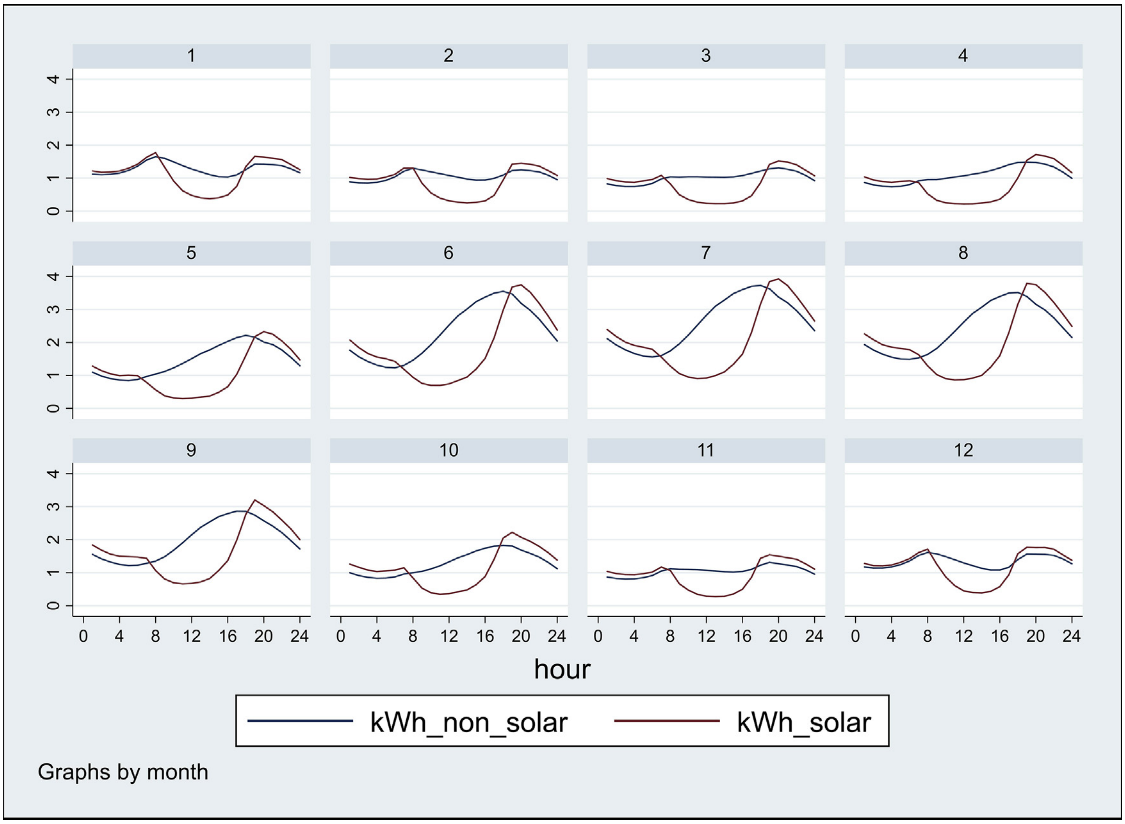


Fig. 3. Hourly electricity delivered from the grid between solar and non-solar customers.

and to be a single-family house. We use having programmable thermostats as a proxy for environmental awareness. Even if this variable is not an ideal proxy, our household-year fixed effects in the panel regression can control for environmental awareness.

4. Empirical strategy

We analyze the causal impact of electricity generated by solar panels on residential consumer electricity consumption. There are two potential threats to identification, related to both the extensive and intensive margins. The first threat is on the extensive margin. Consumers choose to install solar panels voluntarily. Certain unobservable features such as environmental awareness can impact the decision to install solar panels, the size of the system, and electricity consumption behaviors. If these factors are time-invariant, then fixed effects can address the problem. However, there is a possibility that these factors might be time-varying. For example, a homeowner can choose to install solar panels at the same time when undergoing other remodeling projects, such as installing energy efficiency measures or adding a pool or other home expansion projects. Based on our RET survey, solar homes in our sample are not likely to also have energy efficient heating, ventilation, and air-conditioning (HVAC) technologies. If there are indeed other types of major energy efficient technologies being installed at the same time with solar panels, then our estimated solar rebound effects are on the lower side because energy efficiency reduces energy consumption.[2] In addition, for all these home improvements projects and other home expansion projects happening together with solar panel installation, we control for such time-variant changes using household-year fixed effects. We also conduct an analysis using only the post-installation data for the treatment group to eliminate the concern from other potential contemporaneous home improvements.

The second potential threat is on the intensive margin. In particular, the amount of solar electricity generation could be endogenous, even conditional on adoption of solar. Unobservables such as roofing directions and tree shades impact both solar electricity generation and electricity consumption. These two endogeneity issues could impose more threats if these confounding unobservables are time-variant. For example, a household could cut its trees to remove shading. If these unobservables are time-variant and household specific, then traditional fixed effects are insufficient to address the challenge. However, tree-cutting behavior is unlikely in Arizona due to its desert environment and the lack of trees in the first place. In addition, when temperature is controlled for, sunshine only affects household energy consumption through the response to the solar electricity production. Thus conditional on adoption, short-run fluctuations in solar electricity production (which is mainly influenced by sunshine) should be exogenous to household electricity consumption. La Nauze (2018) makes the same assumption. This further ensures that solar electricity production in the short run, after we control for household-year fixed effects and temperature, should be exogenous. To summarize, we adopt a combination of matching and panel regression with household-time-variant fixed effects to address potential endogeneity issues.

In our main model to estimate rebound effects using daily data, since household fixed effects are used, the rebound effect estimates are representing the intensive margin. Our main source of variation is to look at how much more electricity solar customers consume on days with greater solar irradiance when solar panels generate more electricity. For hourly level analysis, we only rely on extensive margin to estimate the change of electricity needed from the grid due to solar panel adoption: we compare the electricity needed from the grid of houses without solar panels to that of houses with solar panels.

4.1. Matching

In order to have comparable control group for solar customers, we adopt a matching approach to approximate a quasi-experimental design (Fowlie et al., 2012; Qiu and Kahn, 2018b). In a matching approach, for each solar customer, we find a non-solar customer that is similar in various characteristics that can impact both solar adoption and energy consumption (Stuart, 2010). These attributes include household income, number of persons in a household, race of household head, age of household head, building square footage, vintage of the building, whether a building has a pool, whether a building has programmable thermostats, dwelling type (single family house, townhouse, apartment/condo, others), ownership status (owner-occupied versus renter-occupied), and electricity rate plans. There are more than 16,000 [3] customers in the RET survey, among which 277 solar customers' information is analyzed in our model.

We use two matching methods: propensity score matching (PSM) and coarsened exact matching (CEM). In propensity score matching, we use logit model to calculate the predicted probability of adopting solar panels for all customers. Then for each solar customer, control customers are assigned weights based on how close the predicted probabilities are to the solar customer. We try different matching algorithms including kernel matching, radius matching with different calipers, and k-nearest neighbors matching. The results of propensity score matching using different algorithms are very similar. We choose to present the results using radius matching which finds a control for a treated individual only within the caliper (0.01). This puts a tolerance level on the largest acceptable propensity score distance. This algorithm yields the smallest median bias. A balancing check is necessary to ensure that the control and treatment groups are indeed comparable after matching. Table A1 in the Appendix shows balancing check results generated by STATA built-in balancing check command *pstest* for PSM and results confirm the balancing.[4]

[2] To give a hypothetical example, assume that the original electricity consumption of a household without any solar panels or energy efficiency upgrades is 40 kWh/day. Now assume that the household only adopts solar panels but no other energy efficiency upgrades, and that the solar panels generate 30 kWh/day. The gross electricity consumption (grid-based consumption + consumed solar electricity) becomes 46 kWh/day. Then without energy efficiency upgrades, the estimated solar rebound effect is (46-40)/30 = 20%. Now assume that together with the solar panel installation, the households also added energy efficiency upgrades. The energy efficiency upgrades lower the gross electricity consumption from 46 kWh/day to 42 kWh/day. If researchers are not aware of these energy efficiency upgrades, then the estimated solar rebound effect is only (42-40)/30 = 6.7%.

[3] To improve the computational efficiency, we randomly selected about 4000 non-solar customers for the matching process.

[4] The variance ratio for "Number of stories" is slightly outside the allowed window [0.78; 1.29]; but according to Rubin (2001), a variance ratio between [0.5, 2] indicates reasonable balancing.

CEM coarsens the variables into strata and then customers are matched based on strata. CEM controls for the amount of imbalance ex ante (Blackwell et al., 2009). To further ensure that the control and treatment groups using CEM are comparable, we use two indicators to evaluate balancing: standardized mean difference (SMD) to check for sample mean and variance ratio (VR) to check for sample variance. $SMD = \frac{|\overline{X}_{Treat} - \overline{X}_{Control}|}{\sqrt{(S^2_{Treat} + S^2_{Control})/2}}$ and $VR = \frac{S^2_{Treat}}{S^2_{Control}}$, *where* $\overline{X}$ is the sample mean and s^2 is the sample variance. To ensure good balancing, VR should be within [0.5, 2] and SMD should be smaller than 0.25 (Rubin, 2001). In Table A2 in the Appendix, VR and SMD are computed and results confirm balancing.

There are two important assumptions of using matching for causal inference. The first assumption is conditional independence − after controlling for covariates **X**, the potential outcomes are independent of the treatment status. This assumption is generally hard to test, so we also combine matching with fixed effects panel regression to get rid of potential confounding unobservables. The second assumption is common support −the probability of a customer adopting solar panels conditional on the observed control variables should be between 0 and 1. For propensity score matching, Figure A3 in Appendix confirms common support. For CEM, all observations within a stratum containing both a treated and control unit are by construction inside of the common support.

4.2. Fixed effects panel regression

Using daily register read data and solar electricity generation data, we analyze the impact of solar electricity generation on daily electricity consumption Cons_d and then measure the rebound effects. We run the following regression on the matched control and treatment group:

$$\text{Cons}_{id} = \alpha_{iy} + \beta_S kWh_{isd} + \gamma p_{id} + f(HDD_{id})\boldsymbol{\theta} + f(CDD_{id})\boldsymbol{\eta} + \delta Holiday_d + Day\ of\ month + Day\ of\ week + month\ of\ year + \varepsilon_{id} \tag{3}$$

where kWh_{isd} is the electricity generated by solar panels for customer i on day d; β_S measures how customer's daily electricity consumption changes with respect to 1 kWh additional solar electricity generated. As discussed in theoretical model, β_S should be equal to price elasticity of demand. From β_S we can also calculate the rebound effects. We include kWh_{isd} in the regression because solar customers can observe accurately the amount of electricity generated by solar panels from their user portal. p_{id} is average daily electricity price calculated based on marginal price. One might argue that customers self-select into different rate plans so that the average daily electricity price variable constructed based on the marginal electricity price can also be endogenous. However, this should not be an issue because we use customer-year fixed effects to control for any unobservables that can impact customers' selection of rate plans. In addition, p_{id} only serves the purpose of a control variable. The variation of the price variable in the regression model comes from two sources. First, seasonal marginal prices of the same price plan (including both TOU and non-TOU) differ by season. Second, there is also cross-sectional variation of marginal prices across different price plans. This price variable serves as a control variable for the attributes of different price plans so this term is identifying the impact of price plans on electricity consumption. HDD is heating degree days as calculated by 65 - temperature; CDD is cooling degree days as calculated by temperature - 65; f is spline function for HDD and CDD[5]; and *Holiday* is an indicator variable for federal official holidays. We include the following fixed effects: α_{iy} is customer-year fixed effect which can control for time-variant unobservables impacting solar adoption and solar generation such as change in building shading conditions, change in other home technologies or attributes, and change in occupancy for each customer at yearly level; a set of time fixed effects including hour of day, day of month, day of week, and month of year which control for factors that change over time for all customers such as change of energy efficiency policies and incentives, and prices of solar panels. Note that *year of sample* is not included since we include customer-year fixed effects. Standard errors are clustered at the customer level to avoid autocorrelation of the error term ε_{id}.

5. Results of main model specifications

In this section we discuss the results of our main model specifications. In Appendix B we also include the results of other model specifications which analyze the impact on net daily electricity purchase as well as how household attributes, cost of panel, and financing mode influence solar customer electricity consumption behaviors.

Our main source of identification is to look at how individual solar consumer's electricity consumption changes when the amount of solar electricity generated by their solar panels changes. Such change in solar panel electricity generation is mainly due to fluctuations in solar irradiance. Thus our primary source of identification is to look at how much more solar households consume on sunnier days when the amount of electricity generated by their solar panels is higher. Figure A4 shows a descriptive positive relationship between individual consumer's gross daily electricity consumption and solar electricity

[5] Hourly temperature data by station is obtained from the National Oceanic and Atmospheric Administration (NOAA)'s Local Climatological Data (https://www.ncdc.noaa.gov/cdo-web/datatools/lcd). We match each customer's zip code with the nearest weather station from NOAA.

Table 2
Impact of electricity generated by solar panels on daily electricity consumption.

PSM sample; All rate plans	Using all time periods for both control and treatment groups			Using only the post-treatment period of the treatment group
	All year	Summer	Winter	All year
Model number	(1)	(2)	(3)	(4)
Daily electricity generated by a solar panel system	0.183***	0.186***	0.138***	0.192***
	(0.035)	(0.037)	(0.034)	(0.034)
Average daily electricity price	−60.448**	−42.526***	−117.341***	−22.077
	(25.032)	(11.984)	(32.472)	(33.962)
Holiday	0.565*	0.501	0.906***	0.868***
	(0.313)	(0.399)	(0.247)	(0.334)
Constant	39.038***	40.952***	42.975***	35.863***
	(1.728)	(1.525)	(2.475)	(2.320)
CDD	Yes	Yes	Yes	Yes
HDD	Yes	Yes	Yes	Yes
Fixed effects				
Account year	Yes	Yes	Yes	Yes
Month of year	Yes	Yes	Yes	Yes
Day of month	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes
N	619,788	313,821	305,967	250,692

Clustered standard errors in parentheses; * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

generation. A key potential issue with this source of identification is that on sunnier days in the summer, the cooling demand is also higher which will translate into higher electricity consumption. Similarly, on sunnier days during the winter, the heating demand could be lower so that the electricity consumption is lower. As a result, adequately controlling for CDD and HDD is very important. In our main model specifications, we use linear spline function to control for CDD and HDD.

5.1. Impact on daily consumption

5.1.1. Overall impact and rebound effects

We now analyze how customers' electricity consumption changes with respect to solar electricity generation. Results are listed in Table 2. Our main discussion is based on results from propensity score matching which gives us larger sample. Model (1) in Table 2 shows the results for all months. The coefficient for solar electricity generation is 0.183, meaning that if solar panels generate 1 kWh additional electricity, the customer will consume 0.183 kWh more electricity. As illustrated in equation (2) in the theoretical framework, we have $\frac{\partial e_{post}}{\partial e_s} = -\xi$. In the regression model $\frac{\partial e_{post}}{\partial e_s}$ is the coefficient for solar electricity generation. Thus, this coefficient should be close to price elasticity.

The rebound effect is defined as the amount of energy savings that is "taken back" by behavioral change. The coefficient that measures the change in electricity consumption in response to the change in solar electricity generation thus measures the rebound effect. In model (1) of Table 2 the coefficient is 0.18. This means for every 1 kWh solar electricity, the increase of 0.18 kWh in total electricity consumption erodes the engineering savings by 18% and thus the coefficient itself measures the solar rebound effect. For Model (2) the coefficient is 0.186 for the summer and in Model (3) the coefficient is 0.138 for the winter, implying that the rebound effect is 18.6% in summer months and 13.8% in winter months.

As discussed earlier one concern for causal identification is that households might undergo contemporaneous home improvement or expansion projects the same time when installing solar panels. Although we use household-year fixed effects to control for such possibility, we now add another analysis where we only use the post-installation data for the treatment group to run the fixed effects regression. This approach relies only on the short-run exogenous variation in solar electricity generation and thus is not confounded by other potential contemporaneous home improvements. Results are listed as Model (4) in Table 2 and the response to an additional 1 kWh solar electricity is 0.19.

It can be relatively straightforward for solar households to observe the amount of daily[6] electricity generated by solar panels by logging into their user portal via a cellphone application or a website. With such daily level information, it is possible that consumers can form a linkage between easily observable solar irradiance (e.g. by looking at the sky) and the amount of electricity produced by solar panels, so that it becomes easier to get a good estimate of daily solar electricity generation even without needing to log into the user portal. With the information on daily solar electricity generation, consumers can get a sense of the amount of electricity that is "free" (not needing to pay for the utility). We follow Ito (2014) and assume that households respond to average electricity price instead of marginal electricity price. Ito (2014) states that to

[6] Our theoretical model is not constrained to only monthly level; it can be applied at daily level, as long as the consumers can have an assessment of the amount of solar electricity and total consumption at daily level.

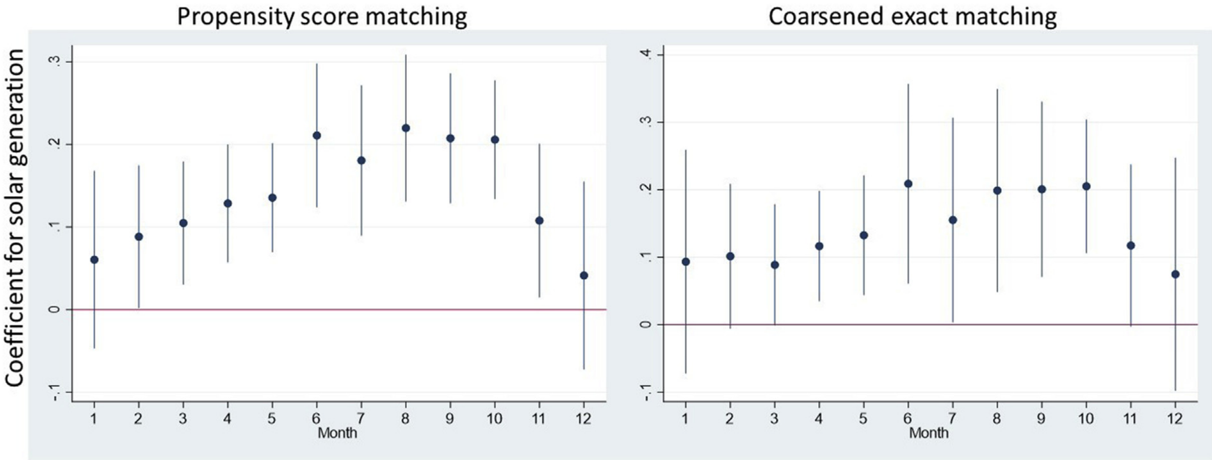


Fig. 4. Impact of solar electricity generation on daily electricity consumption. Notes: Blue dots indicate the value of coefficients for *Electricity generated by a solar panel system* for that month; Vertical blue lines indicate 95% confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

get the perceived average electricity price, households simply use the total payment divided by total consumption. When consumers get a sense that the amount of solar electricity generation on a given day is large, they will think that the portion of free electricity is also large (consumers can also get the information of their gross daily electricity consumption[7] from their portal so they know the "portion" of free solar electricity among total electricity consumption), and then the average price should be low on that day because the average price goes down as the portion of solar electricity goes up. As a result, with intuition solar consumers can get a sense of average electricity price fluctuations even if they are naïve about the pricing structure and how their actual bills are calculated by the utility company. The monthly level analysis shows a similar rebound effect at 14% (Table A3). However, since daily level analysis controls for account-year fixed effects which better control for time-variant unobservables at the individual household level, we use the 18% rebound effect found from daily level analysis as our main result.

For CDD spline, the number of knots is 4 such that the data is divided into 5 equal-width groups of CDD for piecewise linear function. The same applies to HDD spline. Figure A5 shows the graphs of how daily electricity consumption changes with daily CDD and HDD using the estimated spline functions. In addition, we tried two other methods to control for CDD and HDD in the regression model: 1) spline function with 4 knots equally spaced based on percentiles of CDD and HDD; and 2) not using spline function but controlling for linear, square, and cubic of CDD and HDD. The results in Table A4 show that the estimated rebound effects are almost the same using different controls of temperature.

5.1.2. Impact by month

We now estimate $\text{Cons}_{id} = \alpha_{iy} + \sum_{M=1}^{12} \beta_{SM} kWh_{isd} {*} I_M + \gamma p_{id} + f(HDD_{id})\boldsymbol{\theta} + f(CDD_{id})\boldsymbol{\eta} + \boldsymbol{\delta} Holiday_d + Day\ of\ month\ + Day\ of\ week + month\ of\ year + \varepsilon_{id}$ to look at the response by month I_M. The coefficients by month are illustrated in Fig. 4. Complete regression results are listed in Table A5 in the Appendix. The general trend is that for 1 kWh additional solar electricity generation, consumers increase their consumption by more kWh in the summer months than they do during the winter months. This could be due to higher price elasticity of demand in the summer than in the winter. There is a large cooling need in the summer months in Arizona. If solar customers know that their effective electricity price is lower due to solar electricity generation, in the summer they might consume more electricity because they can now make their room temperature more comfortable for longer periods of time during hot summers. In contrast, there is not much need for improvement through consuming more electricity for heating during winters because Arizona winters already have a mild temperature (in the coldest months of January and February, the average low temperature is 43.4F while the average high temperature is 65F). As a result, consumers' electricity demand is more price elastic in the summer.

5.1.3. Validity test

Out of the 277 solar customers analyzed in our paper, 81 adopted solar panels between 2013 and 2017. For these customers, we observe both their pre-installation and post-installation energy consumption patterns. In our main analysis, we

[7] Here are two examples showing the type of information available on user portal for a solar consumer: https://www.locusenergy.com/solutions/software/solarnoc%E2%84%A2/site-owner-application https://itunes.apple.com/us/app/solaredge-monitoring/id384374347?mt=8.

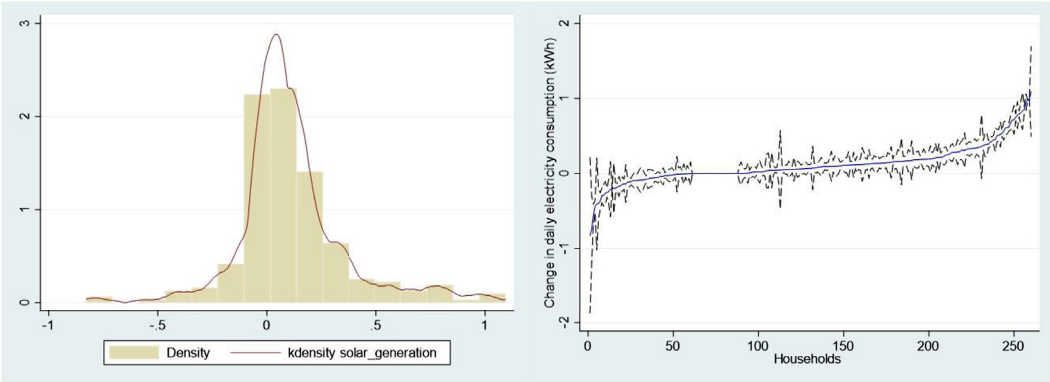


Fig. 5. Distribution of the impact of solar electricity generation on daily electricity consumption. Notes: The left figure shows the histogram of the coefficients for solar electricity; the right figure shows the 95% confidence intervals of the coefficients.

include solar customers who installed the panels prior to 2013 and thus lack the pre-installation energy consumption data for these customers. In order to help check the validity of the analysis including solar customers with only post-installation energy consumption data, we conduct a separate analysis for the 81 solar customers and compare the results with those in our main analysis. For this validity check, we add the pre-installation average daily energy consumption as a matching variable. To calculate the pre-installation consumption data for non-solar customers, we randomly assign solar installation dates to these non-solar customers. Then using the matched control and treatment customers, we run similar fixed effects panel regression models.

Figure A6 in the Appendix shows the change in electricity consumption in response to an additional 1 kWh solar electricity.[8] Results are consistent with those using all 277 solar customers. Larger rebound effects happen during summer months compared to winter months. On average, based on regression results for Model 1 in Table A6 in the Appendix, when using the solar customers with both pre- and post-installation energy consumption data and with pre-installation energy consumption added as a matching variable, the coefficient for solar electricity generation is 0.146 and is statistically significant at 5% level. This coefficient is of a similar magnitude as 0.183 which is the coefficient for solar electricity generation when using all solar customers. We then further check that there is no systematic difference in energy consumption patterns prior to solar installations between the treatment and control groups, using the regression model

$$\mathrm{Cons}_{id} = \beta * Solar_i + \gamma p_{id} + f(HDD_{id})\boldsymbol{\theta} + f(CDD_{id})\boldsymbol{\eta} + Day\ of\ month + Day\ of\ week + month\ of\ year + year\ of\ sample + \varepsilon_{id},$$

where Cons_{id} is the daily electricity consumption prior to solar installations; $Solar_i$ indicates whether a customer belongs to the treatment group or not. Results for Model 2 in Table A6 show that the coefficient for $Solar_i$ is not statistically significant, indicating that the pre-installation electricity consumption patterns are similar between the control and treatment groups. In addition, we plot the time trend for the weighted average monthly electricity consumption for the control and treatment group. Figure A7 shows that in 2013 when there were relatively few solar adopters, the monthly energy consumption trends between the control and treatment groups were very similar. Starting 2014 when more and more customers adopted solar panels, the average consumption of control group became lower than that of the treatment group.

5.1.4. Heterogeneity: distributions of impacts

In order to examine the distributions of impacts on electricity consumption among solar customers, for each solar customer we regress daily electricity consumption on solar electricity generation, controlling for HDD, CDD, price, holiday, and same sets of time fixed effects. For a total of more than 200 regression models, we obtain the key coefficients for each solar customer. In Fig. 5, we draw the histogram and 95% confidence intervals of the coefficient that measures the change in electricity consumption in response to 1 kWh additional solar electricity generation. Some solar customers show rebound effects (positive coefficients) while some other solar customers reduce their electricity consumption. We show next that this could be due to environmental ideology.

5.1.5. Heterogeneity: impact by environmental ideology

We download the zip-code level voter registration data from Maricopa county website.[9] For each electric customer, we do not have the exact address but only the zip code, so we can only use the zip code level voter registration data to merge with

[8] We only show results from using PSM matching because it gives us a reasonably large sample (75 treatment customers and 3141 control customers) while CEM only leaves 15 treatment and 29 control customers.

[9] https://recorder.maricopa.gov/voterregistration/redirect_new.aspx?view=zip.

each customer. We assume that liberal voters will be more likely to be pro-environment (Cragg et al., 2013; Dastrup et al., 2012). We calculate the share of liberal voters in a zip code using

$Liberal = \frac{Registered\ democrat\ voters + Registered\ Green\ party\ voters}{Total\ number\ of\ registered\ voters}$. We use *Liberal* as a proxy for environmental ideology. We then run regression model in electricity consumption adding interaction terms between solar panel adoption and environmental ideology. Results are listed in Table B4. The coefficient for the interaction term is negative and statistically significant, indicating that consumers located in more liberal neighborhoods experience lower rebound effects. This is consistent with existing literature such as Costa and Kahn (2013) that environmental ideology plays a role in consumer energy consumption behaviors. More environmentally aware consumers might pay more attention on conserving energy and as a result after adopting solar panels, they might intentionally adopt other conserving activities as well.

5.1.6. Robustness check: price variable

The price variable constructed in this study is based on the marginal price only and does not depend on each individual customer's consumption pattern, in order to avoid the issue of endogenous average price issues. To show the robustness of our estimation for the key coefficient of interest − the response to solar electricity generation, we remove the price variable in the regression. Results in Table A7 show that removing the price variable does not impact the coefficient for solar electricity generation. In addition, we add an interaction term between price and a dummy variable indicating whether a price plan is TOU or not. The coefficient for solar electricity generation remains 0.18. The interaction term between TOU and price is positive meaning that households with TOU pricing are less sensitive to the electricity price than non-TOU consumers. This might be due to the fact that non-TOU consumers in our sample are on increasing-block pricing so they might need to pay extra attention than TOU consumers to prices because the average price increases as they consume more electricity in a given month. We then interact TOU with solar electricity generation and find that the interaction term is indeed negative (rebound effects are lower) although it is not statistically significant.

5.1.7. Robustness check: machine learning

We use classification and regression trees (CART)-based propensity score model to identify control and treatment groups. The CART-based propensity score model has the ability to better deal with interaction and non-linearity of key attributes (Lee et al., 2010). It is also better than traditional propensity score model which is sensitive to misspecifications. The regression model run on the matched control and treatment group from CART model shows that the coefficient for solar electricity generation is still 0.18 (see Table A7). Table A8 shows the balancing check. Second, we use LASSO and Ridge to predict the electricity consumption of each customer in all time periods using their electricity consumption data in the pre-treatment period. For solar customers in the post-treatment period the predicted value without solar electricity generation is the counterfactual electricity consumption. The predictors include household characteristics, temperature, location, and time indicator variables. Then we regress the differences between the actual value and the predicted value for each customer on the amount of solar electricity generation. The coefficient for solar electricity obtained this way is around 0.16 (see Table A7).

5.1.8. Robustness check: solar irradiance

In order to justify the assumption that sunshine only affects household electricity consumption through the response to solar electricity production, we conduct two additional robustness checks. First, we regress the electricity consumption of non-adopters on solar irradiance (Direct Normal Irradiance, DNI)[10] while controlling for CDD and HDD splines and other variables and fixed effects same as in the main model. Second, for each non-adopter, we create a hypothetical solar electricity generation variable using the actual solar generation of the matched solar adopter. We then regress the electricity consumption of non-adopters on the hypothetical solar electricity generation while controlling for the same set of control variables. If after controlling for temperature and other variables, the solar irradiance and the hypothetical solar electricity do not have statistically significant impact on the electricity consumption of non-solar consumers, then it justifies that indeed our main finding of the response to solar electricity generation of solar consumers is all due to rebound effects rather than direct impact of solar irradiance. Results in Table A7 confirm that solar irradiance does not have statistically significant impact on electricity consumption after controlling for temperature and other key variables and fixed effects. The same applies to the hypothetical solar electricity variable. If a household has the tendency to close blinds and curtains on a sunny day, then that habit and tendency can be captured by the household-year fixed effects so that the average electricity consumption of these households with such habits will be different than households without such habits in our model.

5.2. Impact on hourly electricity delivered to customers

We now look at the impact on hourly electricity delivered from the grid to customers which reflects how much electricity the utility company needs to purchase from electricity generators or from electricity trading in a given hour, after any

[10] The DNI solar irradiance data is obtained from the National Solar Radiation Data Base maintained by National Renewable Energy Laboratory (NREL) https://maps.nrel.gov/nsrdb-viewer. We match each zip code with the nearest location with NREL solar irradiance data. Whenever there is a lack of solar irradiance data for a given time period for a given location, we use the NREL simulated solar irradiance data for a given day in a typical meteorological year as a replacement for that location.

behavior change such as rebound effects. kWh_{ch} can be used to calculate emissions associated with the electricity that the utility company needs to purchase for its customers. We use the following panel regression:

$$kWh_{ich} = \alpha_{iy} + \sum_{H=1}^{24} \beta_H Solar\ panel_{ih} {*} I_H + \gamma p_{ih} + f(HDD_{ih})\boldsymbol{\theta} + f(CDD_{ih})\boldsymbol{\eta} + \delta Holiday_d + \ Hour\ of\ day + Day\ of\ month + Day\ of\ week + month\ of\ year\ + year\ of\ sample + \varepsilon_{ih} \tag{4}$$

where i indicates individual customer; h indicates hour of sample;H indicates hour of day; I_H is an indicator variable for each hour of day;$Solar\ panel_{ih}$ is equal to 1 if customer i has solar panels installed at h; p_{ih} is marginal electricity price based on SRP's price plan for customer i at h. The key coefficients of interest are the series of β_H which measure the change in hourly kWh delivered from the grid to the customer after adopting solar panels.

Running regression equation (4), we obtain the coefficients that measure the impact of solar panel adoption on each hour's electricity delivered to the customers. We show the values and 95% confidence intervals of these coefficients in Fig. 6. A negative and statistically significant coefficient means that there is a reduction in electricity needed from the grid. The coefficients for all variables in regression equation (4) are listed in Table A9 in Appendix. There are two key takeaways from Fig. 6. First, in terms of the magnitude of reduction, in the summer, the maximum hourly reduction happens at 2pm with a 2.2 kWh/hr reduction. In the winter, the maximum hourly reduction happens at noon and 1pm with a 1.19 kWh/hr reduction. Second, in the winter there is a reduction in electricity needed from the grid even during evening hours. This could be due to the fact that solar panels could potentially function as adding strengthened insulation to the roof. As illustrated in engineering studies (e.g. Dominguez et al., 2011), during the daytime, ceiling temperatures under PV panels in solar homes are lower compared to those of non-solar roofs, while during nighttime ceiling temperatures are higher. This will reduce heating needs during winter evening hours, while it will not reduce cooling needs during summer evening hours because of higher ceiling temperatures. In Arizona, 58% of homes use electric heating (EIA, 2009), which helps explain why there is reduction of electricity delivery for solar homes during winter evening hours.

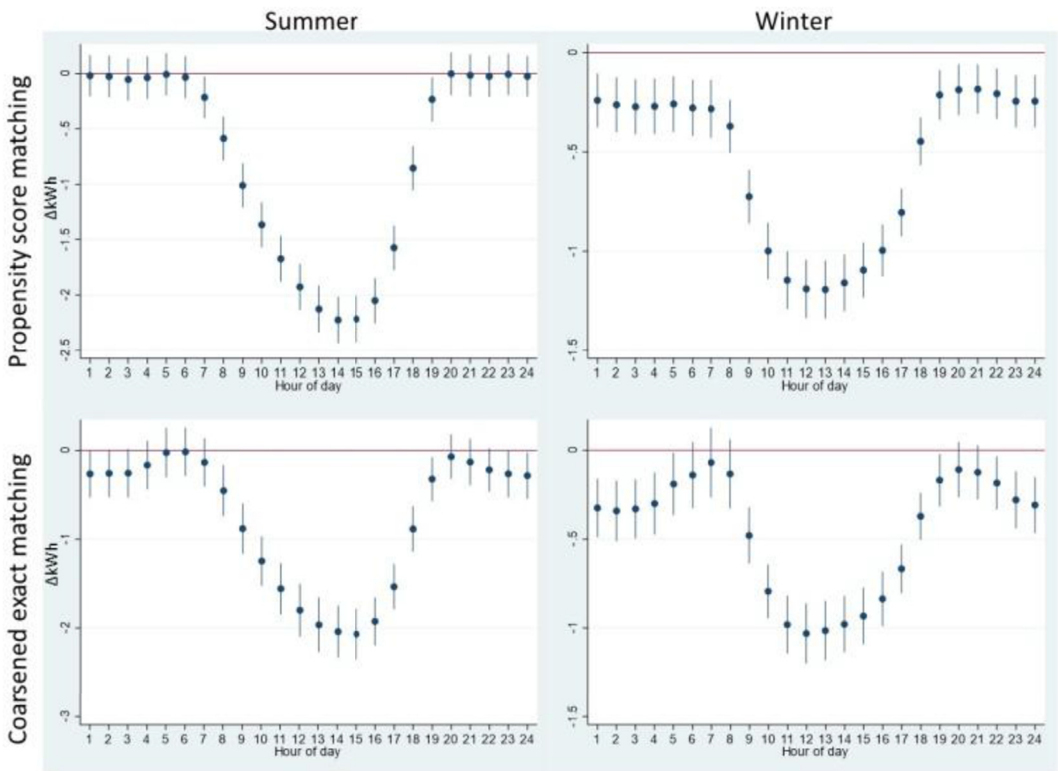


Fig. 6. Change in hourly electricity delivered from the grid due to solar panel adoption. Notes: Blue dots indicate the value of coefficients for *Solar panel adoption* for that hour; Vertical blue lines indicate 95% confidence intervals; Summer months are May–October and winter months are the rest months. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

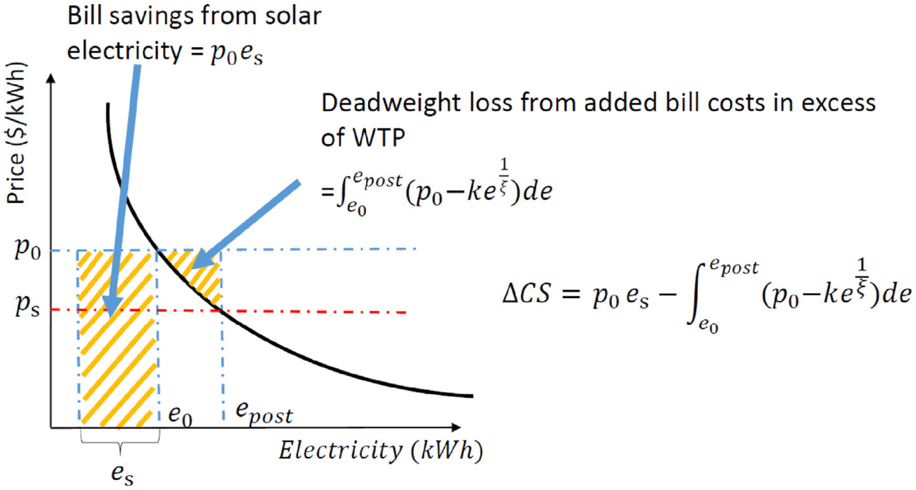


Fig. 7. Consumer surplus calculation. Notes: The change in consumer surplus is the benefit of bill savings minus the deadweight loss from incremental consumption which is the added bill costs in excess of willingness to pay (WTP).

6. Discussions

6.1. Consumer surplus change

Building upon our theoretical model in Section 2, assuming constant elasticity of electricity demand near the price regions around p_0 and p_s, then the constant price elasticity demand curve should be $p = \frac{k}{e^{-\frac{1}{\xi}}} = ke^{\frac{1}{\xi}}$.[11] Now to find what k is equal to, we know that at p_0, the consumption level is e_0. So we have $p_0 = ke_0^{\frac{1}{\xi}}$. Thus, $k = p_0 e_0^{-\frac{1}{\xi}}$.

Consumers think that they are paying a reduced effective average price of p_s so they increase their gross consumption from e_0 to e_{post} but in fact for the incremental consumption $(e_{post} - e_0)$ they are actually paying p_0. Consumers' willingness to pay (WTP) as measured by the demand curve for the increased consumption is lower than what they are paying (p_0). As a result, there is a deadweight loss from incremental consumption which is equal to the added bill payment minus the value of the incremental consumption to consumers. As Fig. 7 illustrates, the change in consumer surplus from generating e_s amount of solar electricity and with rebound effects is the benefit of bill savings $(e_s p_0)$ minus the deadweight loss ($\int_{e_0}^{e_{post}}\left(p_0 - ke^{\frac{1}{\xi}}\right)de$).

The total change in consumer surplus is $\Delta CS = p_0 e_s - \int_{e_0}^{e_{post}}\left(p_0 - ke^{\frac{1}{\xi}}\right)de$. Since $k = p_0 e_0^{-\frac{1}{\xi}}$, the final change in consumer welfare as a function of known parameters is

$$\Delta CS = p_0 e_s - \left[p_0(e_{post} - e_0) - p_0 e_0^{-\frac{1}{\xi}}\left(\frac{\xi}{1+\xi}e_{post}^{\frac{1+\xi}{\xi}} - \frac{\xi}{1+\xi}e_0^{\frac{1+\xi}{\xi}}\right)\right]$$

We will then use our estimated parameters from empirical analysis to calculate the change in consumer surplus from solar panel adoption. Recall we have $\frac{\partial e_{post}}{\partial e_s} = -\xi$. We use the coefficient for solar electricity generation as the value for $-\xi$ to calculate change in consumer welfare. From model (1) in Table 2, ξ = -0.183. On average, the electricity price before solar adoption is \$0.1/kWh; the daily electricity consumption before solar adoption is 37.8 kWh/day; the daily electricity consumption after solar adoption is 46.6 kWh/day; and the average daily solar electricity generation is 30.3 kWh/day. Plug in all the parameters, the daily change in CS = 0.1*30.3-(0.1*(46.6–37.8)-0.1*37.8(-1/(-0.183))*((-0.183)/(1–0.183)*46.6((1–0.183)/(-0.183))-(-0.183)/(1–0.183)*37.8((1–0.183)/(-0.183)))) = \$2.664/day. Then for a year, the increase in consumer surplus is \$2.664*365 = \$972/year. Based on the sample in this study, on average, solar panel systems cost \$5176*6.61 = \$34,213. A simple payback period assuming a zero discount rate is thus 35 years. From the main model specification Model (1) in Table 2, the coefficient for the price variable γ is −60.4. At the average price level of \$0.1/kWh and average electricity consumption

[11] We have $e = \left(\frac{k}{p}\right)^{-\xi}$. $\xi = \frac{\partial e}{\partial p}\frac{p}{e} = \frac{\partial\left(\frac{k}{p}\right)^{-\xi}}{\partial p}\frac{p}{e} = -\xi\left(\frac{k}{p}\right)^{-\xi-1}k\left(-\frac{1}{p^2}\right)\frac{p}{\left(\frac{k}{p}\right)^{-\xi}} = -\xi\left(\frac{k}{p}\right)^{-1}k\left(-\frac{1}{p}\right) = \xi$

level of 37.8 kWh (from Table 1), the price elasticity is equal to $\gamma \frac{\bar{p}}{cons}$ = -60.4*0.1/37.8 = -0.16 which is close to the estimated rebound effects. We then test the equality statistically and the F-test (p value 0.5096) fails to reject that the coefficient for solar electricity is equal to the estimated price elasticity.

Without considering the rebound effects, we can use the value of solar electricity as the change in consumer surplus when consumers do not change their gross electricity consumption (no rebound). At the average electricity price and at the average amount of daily solar electricity generation, such increase in consumer surplus is $3.03/day or $1106/year without considering solar rebound effects. The estimated difference in the consumer surplus change calculations between ignoring rebound effects and considering rebound effects is 12%.

6.2. *Environmental impact evaluation*

We now use the results from hourly analysis to evaluate the environmental impact from solar panel adoption. Our environmental impact evaluation is more precise because we consider solar rebound effects, which will partially offset the environmental benefits from the amount of electricity generated by solar panels. Estimating savings in electricity delivered from the grid at an hourly level can help better evaluate the environmental impact. Marginal emissions factors and marginal damages of air emissions from electricity supply differ intra-day (Holland et al., 2016), and saved electricity from solar panels will have different environmental impacts by hour of day. We use the annual average marginal emissions factors at an hourly level for Western Electricity Coordinating Council (WECC), where Arizona is located, from Holland et al. (2016). The main assumption is that electricity saved in a given location in WECC has the same impact as that saved elsewhere in WECC due to electricity trading. We choose to look at the key types of air emissions including CO2, SO2, NOX and particulate matter. We multiply the hourly marginal damages by hourly saved electricity delivered from the grid. Table A10 in the Appendix show the detailed calculation of the environmental impact. Results show that on average, each solar panel can reduce environmental damage from CO2, SO2, NOX and particulate matter by a total of $122 per year (2000 U.S. dollar, or $178 in 2018 U.S. dollar).

We then calculate the environmental benefit from an average sized solar panel system in our sample if we use a naïve model of electricity consumption that fails to consider solar rebound effects. In this case, the average hourly solar electricity is equal to the amount of hourly reduction in electricity needed from the grid. We then multiply the hourly solar electricity by the marginal damage factor for each environmental pollutant to obtain the overall environmental impact. Results are listed in Table A11. We show that without considering solar rebound effects, the environmental benefit of an average sized solar panel in Phoenix is $162 per year (2000 U.S. dollar) compared to the actual environmental benefit of $122 when we do consider solar rebound effects. The difference in avoided environmental damage estimates between these two methods is statistically significant based on the F-test (p value = 0.0001). Such difference is also economically significant as illustrated by the following calculation. For SRP's service territory there are about 20,000 residential solar consumers. Then for SRP's service territory alone, ignoring rebound effects can over-estimate the environmental benefits of distributed solar panels by $0.8 million/year (calculated by 20,000*(162-122)). Assuming a lifetime of 20 years of solar panels and a 3% discount rate, the difference in lifetime environmental benefit estimates is equal to $11.9 million. Difference of such magnitude in the expected environmental benefit of solar panels suggests that ignoring or being unaware of the rebound effect will likely lead to suboptimal policy. One immediate implication is when policy makers consider incentivizing distributed solar panel installation in the future, they should perhaps structure the incentives contingent on overall post-installation electricity consumption in addition to post-installation solar electricity generation. In addition, when evaluating the contributions of different technologies in carbon emissions reduction target and in reducing other environmental pollutants, the contribution from residential distributed solar should be discounted from the contribution calculated by engineering estimates. This means the cost-effectiveness of different technology options in terms of carbon reduction and thus the policy priority of deploying other technologies relative to residential distributed solar will change. Furthermore, such difference implies that policy makers should put more emphasis on cleaning the electric grid, meaning reducing the emission factors of utility-scale electricity generation, so that the increase in electricity consumption due to solar rebound effects is associated with smaller environmental and carbon footprints.

6.3. *Literature review and our contributions*

Our paper contributes to mainly two strands of energy and environmental economics literature. First, an emerging strand of literature examines the impact of energy technology adoption on electric load profile and thus better estimates the private and social benefits of such adoption (Qiu and Kahn, 2018a; Qiu and Patwardhan, 2018; Novan and Smith, 2018; Boomhower and Davis, 2017). These studies focus on the impact of energy efficiency on hourly energy consumption profiles. Compared to most existing studies that use aggregate monthly energy consumption data, using hourly data provides a more precise evaluation of the private and social benefits of energy-efficiency measures because the marginal emissions factors, the capacity values, and the marginal cost of providing electricity vary throughout the day (Holland et al., 2016; Siler-Evans et al., 2012). Our study joins a few other solar studies (e.g., Gowrisankaran et al., 2016; Mau and Jahn, 2006) by looking at the impact of solar panel adoption on the electricity load profile using actual energy consumption data (and thus considering behavior changes) and solar electricity generation, instead of just using simulated solar production data.

Second, there has been little empirical evidence on the impact of solar panels on subsequent consumer electricity consumption behavior, although there have been an increasing number of empirical studies examining the adoption decisions of solar panels among residential consumers (e.g., Bollinger and Gillingham, 2012; Graziano and Gillingham, 2014; Noll et al., 2014; Reeves et al., 2017; Liang et al., 2018a). The only four other papers that explore solar customer electricity consumption behaviors at a household level using large sample of households are Deng and Newton (2017), La Nauze (2018), McKenna et al. (2018) and Pless and McKenna (2018). We already discussed our contributions compared to Deng and Newton (2017) in the introduction.

The working paper by La Nauze (2018) uses high frequency smart meter data from 2012 to 2013 of 528 households with solar panels in Victoria, Australia to examine household electricity consumption in response to electricity price and income from selling electricity to the grid. Our paper provides new contributions to the literature compared to La Nauze (2018) in the following ways. First, our study has the actual hourly solar generation data for each solar panel system in our sample. In contrast, the solar generation data and thus gross household consumption data in La Nauze (2018) are predicted or computed solar generation data based on solar radiation, other weather data, solar panel attributes, and building attributes. Numerous studies show that such computations can be different from the actual solar electricity generation data (Leloux et al., 2012; Oozeki et al., 2010). Thus, our paper provides more precise analysis of solar customers' gross electricity consumption behaviors compared to La Nauze (2018). Second, our paper looks at both the extensive and intensive margin of solar panels. La Nauze (2018) only has the data on solar customers (and lacking control customers) and thus focuses on the intensive margin.

McKenna et al. (2018) use annual solar generation for about 300 customers in UK and find that solar customers consume about 45% of the electricity generated by solar panels. The working paper by Pless and McKenna (2018) uses 15-min interval data for same sample of households to analyze the impact of providing in-home displays showing solar generation information on solar customers' self-consumption of solar electricity generation (where self-consumption is the amount of solar-generated electricity consumed by customers instead of sold back to the grid). Our study also differentiates from these two UK studies in the following ways. First, we focus on gross energy consumption (electricity purchased from the grid − electricity sold to the grid + solar electricity generation) instead of self-consumption (solar electricity generation − electricity sold to the grid). Gross consumption is needed in order to quantify precisely the rebound effect. Only looking at self-consumption is insufficient for rebound effect analysis because if consumers increase their consumption by more than the amount generated from solar panels, then self-consumption cannot reflect that extra amount exceeding solar generation. Second, there are no control customers (non-solar customers) in McKenna et al. (2018) and Pless and McKenna (2018).

7. Conclusions and policy implications

We examine the impact of solar panels on consumer electricity consumption behaviors. We estimate that when solar electricity generation increases by 1 kWh, solar homes increase their total electricity consumption by 0.18 kWh. Our empirical exercise is for Phoenix Arizona only. There are two unique attributes of this region: 1) high solar irradiance; 2) high cooling needs but low heating needs. While our results have implications for other similarly warm and sunny regions such as Texas and Florida, caution is needed when extending our results to regions with different climates. When solar irradiance is on average very high which translates into a higher amount of solar electricity generation, consumers might be more likely to be under the impression that they are facing lower average electricity price and thus more likely to have rebound effects. In addition, when electricity consumption is high especially in the summer due to high cooling needs, the marginal electricity consumption might be more elastic so the rebound effects could be higher in Arizona in the summer than other regions. For example, when electricity consumption is high, on the margin, change in electricity consumption could be due to change in thermostat settings rather than change in usage from other appliances such as dish washer, lighting, or refrigerator. Change in thermostat settings is relatively easy and straightforward, making electricity consumption more elastic and rebound effects larger.

Our results have important policy implications. First, in terms of evaluating the impacts of distributed solar panel adoption, ignoring rebound effects can miscalculate these impacts. For the benefits to consumers, we demonstrate that ignoring rebound effects can miscalculate the increase in consumer surplus by 12%. For environmental benefits, ignoring rebound effects can over-estimate the values of solar panels in reducing the major environmental pollutants and carbon emissions. When evaluating the contribution of distributed solar energy for helping states meet their Renewable Portfolio Standard (RPS), rebound effects indicate that it will take more efforts to meet RPS than before when rebound effects were not considered. Similarly for any other evaluations that involve the impact of distributed solar on energy consumption (e.g. such as the economic evaluation in Holland et al. (2018)), rebound effects need to be considered. Currently systems simulation models such as climate models and integrated assessment models (e.g. MARKAL) have considered rebound effects from energy efficiency improvements. Our paper points out that rebound effects from solar panels should also be explicitly considered in simulation models.

Second, as discussed in the Introduction, a key debate around distributed solar energy concerns the distributional impact among different parties. This includes a potentially negative impact on electric utilities and non-solar customers. Solar customers reduce their electricity payment to the utilities. For residential rate plans that do not have demand charges, utilities rely on kWh sales to recover the cost of infrastructure needed to supply electricity to these residential customers. Thus, reduced bills from solar customers mean that utilities need to increase their per kWh prices to recover upfront investment (Johnson et al., 2017). This leads to discussion of subsidization of solar adopters (who are likely to already enjoy higher income) by non-solar customers (who are more likely to have lower income). Our finding of 18% rebound effects from solar customers imply that when calculating the necessary increase in electricity rates and/or demand charge, utilities and policy makers need to consider the increase in electricity consumption from solar customers. This implies that previously discussed problem of “subsidizing the rich” should be mitigated by about 18%.

Third, our estimated payback period is more than 30 years without considering financial subsidies. A 30 + year payback is long enough to deter private investment in solar panels. Based on Census population statistics (Qiu et al., 2014), on average in Arizona, people only stay in the same house for 9 years. Homeowners face the risk of how much the solar panels can be valued in housing prices when they resell their houses. Our study implies that even in Arizona, where solar radiation is abundant, distributed solar panels are still not financially attractive without government subsidies. The cost of solar panels still needs to continue to drop or subsidies are still needed to accelerate adoption.

Fourth, we estimate that the environmental benefit on average per solar panel system is $178/year (2018 USD). Assuming a lifetime of 20 years of solar panels and a 3% discount rate, the lifetime environmental benefit is then equal to $2650 (2018 USD). If the lifetime assumption increases to 30 years, the environmental benefit is $3491(2018 USD). The total social benefit of distributed solar panel installation should also consider any benefits enjoyed by the electricity supply infrastructure and also the knowledge spillover during the technology diffusion (Verdolini and Galeotti, 2011). Thus the subsidies to a solar panel system in Arizona should at least be on the magnitude of $2600-$3400 (2018 USD), when considering only the externality associated with carbon and environmental pollution. Currently the financial subsidies for a typical solar panel system are $5000-$9000 (SEIA, 2014).

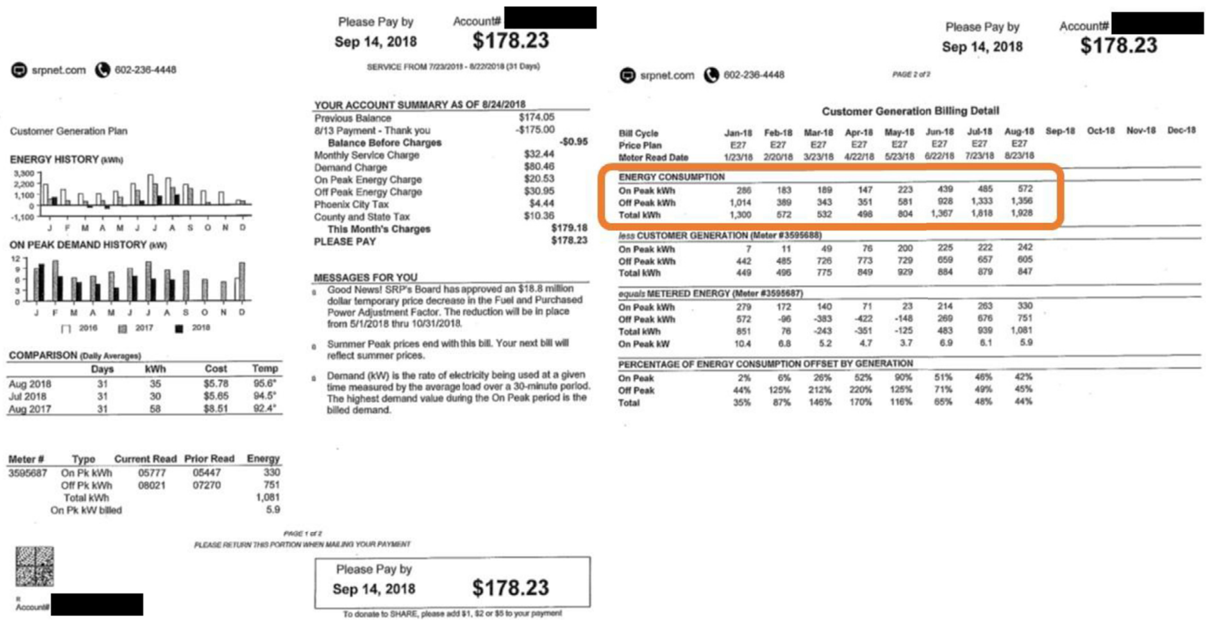
Conflicts of interest

There is no conflict of interest.

Financial disclosure statement

There is financial disclosure applicable.

Appendix A



Please Pay by Sep 14, 2018 Account# [redacted] $178.23

SERVICE FROM 7/23/2018 - 8/22/2018 (31 Days)

srpnet.com 602-236-4448

Customer Generation Plan

ENERGY HISTORY (kWh)

3,300 2,200 1,100 0 -1,100

J F M A M J J A S O N D

ON PEAK DEMAND HISTORY (kW)

12 9 6 3 0

J F M A M J J A S O N D

2016 2017 2018

COMPARISON (Daily Averages)

	Days	kWh	Cost	Temp
Aug 2018	31	35	$5.78	95.6°
Jul 2018	31	30	$5.65	94.5°
Aug 2017	31	58	$8.51	92.4°

Meter #	Type	Current Read	Prior Read	Energy
3595687	On Pk kWh	05777	05447	330
	Off Pk kWh	08021	07270	751
	Total kWh			1,081
	On Pk kW billed			5.9

YOUR ACCOUNT SUMMARY AS OF 8/24/2018

Previous Balance	$174.05	
8/13 Payment - Thank you	-$175.00	
Balance Before Charges		-$0.95
Monthly Service Charge	$32.44	
Demand Charge	$80.46	
On Peak Energy Charge	$20.53	
Off Peak Energy Charge	$30.95	
Phoenix City Tax	$4.44	
County and State Tax	$10.36	
This Month's Charges		$179.18
PLEASE PAY		$178.23

MESSAGES FOR YOU

- Good News! SRP's Board has approved an $18.8 million dollar temporary price decrease in the Fuel and Purchased Power Adjustment Factor. The reduction will be in place from 5/1/2018 thru 10/31/2018.
- Summer Peak prices end with this bill. Your next bill will reflect summer prices.
- Demand (kW) is the rate of electricity being used at a given time measured by the average load over a 30-minute period. The highest demand value during the On Peak period is the billed demand.

PAGE 1 of 2

PLEASE RETURN THIS PORTION WHEN MAILING YOUR PAYMENT

Account# [redacted]

Please Pay by Sep 14, 2018 $178.23

To donate to SHARE, please add $1, $2 or $5 to your payment

Please Pay by Sep 14, 2018 Account# [redacted] $178.23

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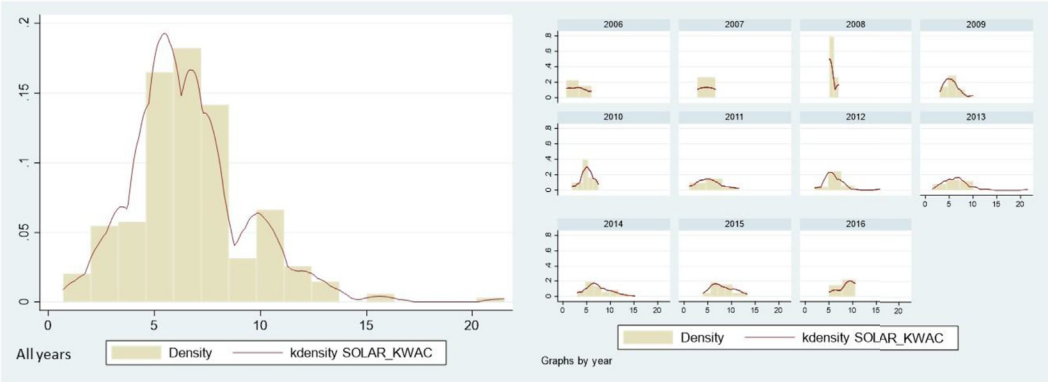
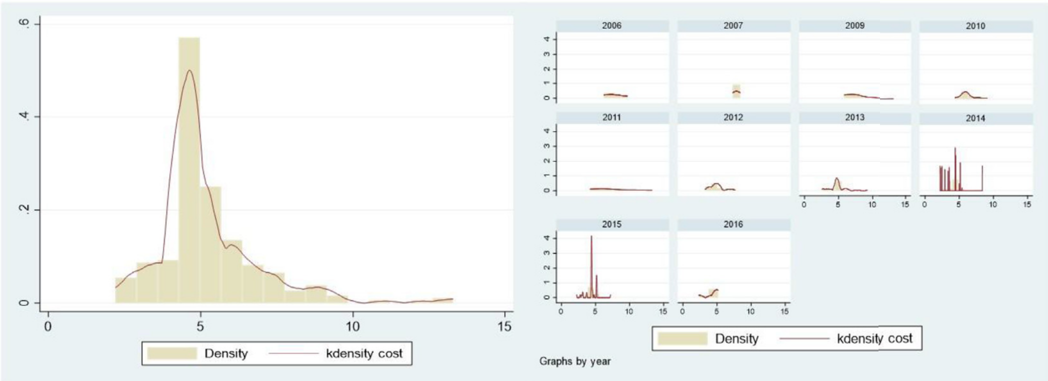
Customer Generation Billing Detail

Bill Cycle	Jan-18	Feb-18	Mar-18	Apr-18	May-18	Jun-18	Jul-18	Aug-18	Sep-18	Oct-18	Nov-18	Dec-18
Price Plan	E27	E27	E27	E27	E27	E27	E27	E27				
Meter Read Date	1/23/18	2/20/18	3/23/18	4/22/18	5/23/18	6/22/18	7/23/18	8/23/18				
ENERGY CONSUMPTION												
On Peak kWh	286	183	189	147	223	439	485	572				
Off Peak kWh	1,014	389	343	351	581	928	1,333	1,356				
Total kWh	1,300	572	532	498	804	1,367	1,818	1,928				
less CUSTOMER GENERATION (Meter #3595688)												
On Peak kWh	7	11	49	76	200	225	222	242				
Off Peak kWh	442	485	726	773	729	659	657	605				
Total kWh	449	496	775	849	929	884	879	847				
equals METERED ENERGY (Meter #3595687)												
On Peak kWh	279	172	140	71	23	214	263	330				
Off Peak kWh	572	-96	-383	-422	-148	269	676	751				
Total kWh	851	76	-243	-351	-125	483	939	1,081				
On Peak kW	10.4	6.8	5.2	4.7	3.7	6.9	6.1	5.9				
PERCENTAGE OF ENERGY CONSUMPTION OFFSET BY GENERATION												
On Peak	2%	6%	26%	52%	90%	51%	46%	42%				
Off Peak	44%	125%	212%	220%	125%	71%	49%	45%				
Total	35%	87%	146%	170%	116%	65%	48%	44%				

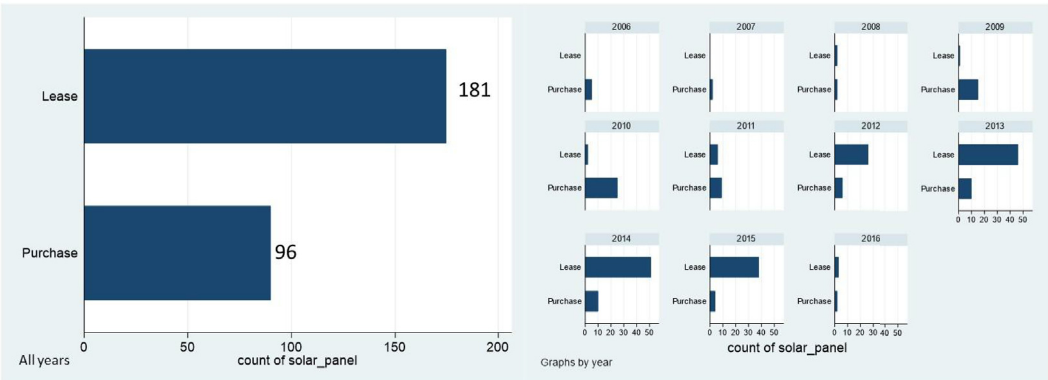
Fig. A1. An example of solar customer electricity bills. Note: The text highlighted in the orange rectangle shows the gross electricity consumption, including both grid-based consumption and consumption of solar electricity.



(a) Distribution of system size in kW (AC)



(b) Distribution of unit cost ($1000/kW)



(c) Distribution of financing mode

Fig. A2. Characteristics of the solar panels analyzed in the study.

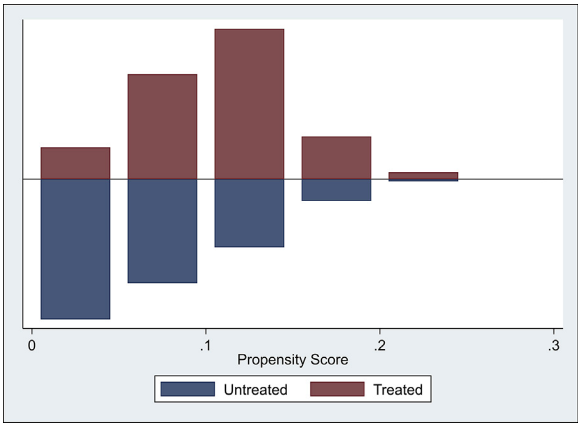


Fig. A3. Check for common support assumption for propensity score matching results.

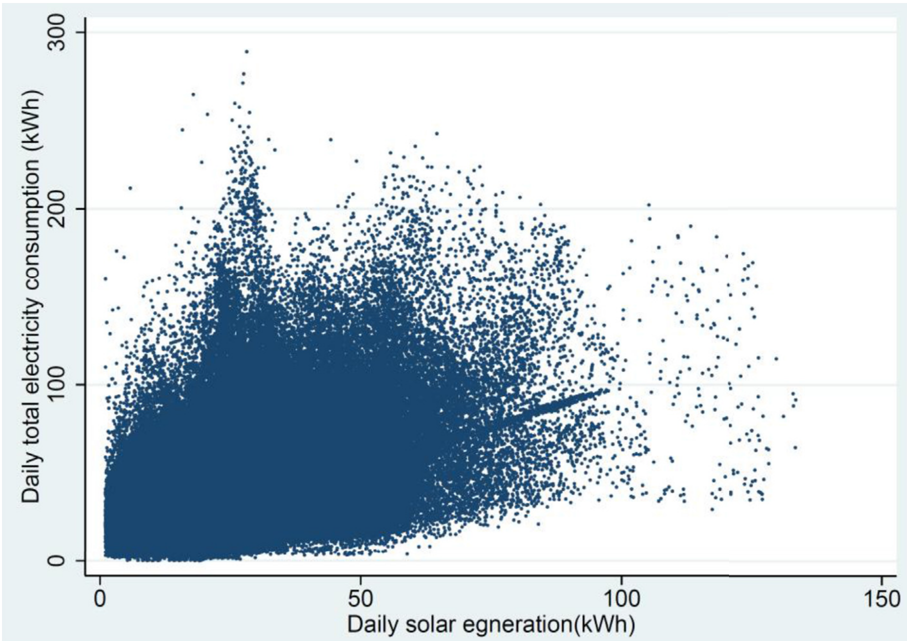


Fig. A4. The correlation between daily solar electricity generation and gross electricity consumption.

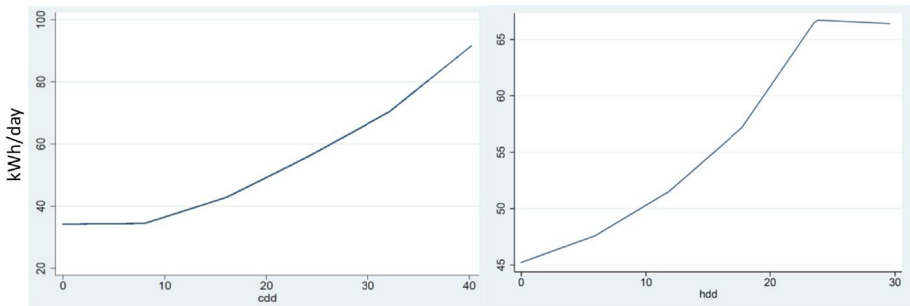


Fig. A5. Estimated spline functions of CDD and HDD.

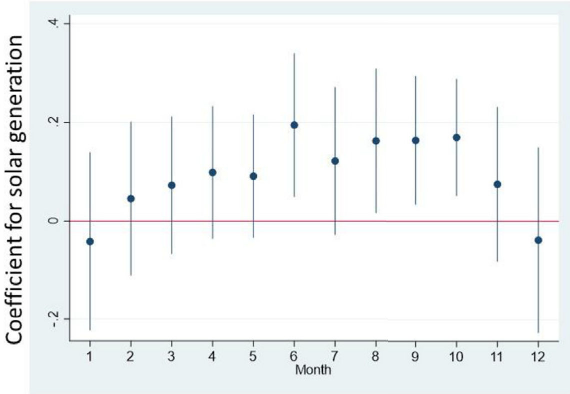


Fig. A6. Impact of solar electricity generation on daily electricity consumption; using only solar customers with both pre- and post-installation energy consumption data. Notes: Blue dots indicate the value of coefficients for *Electricity generated by a solar panel system* for that month; Vertical blue lines indicate 95% confidence intervals; Using propensity score matching.

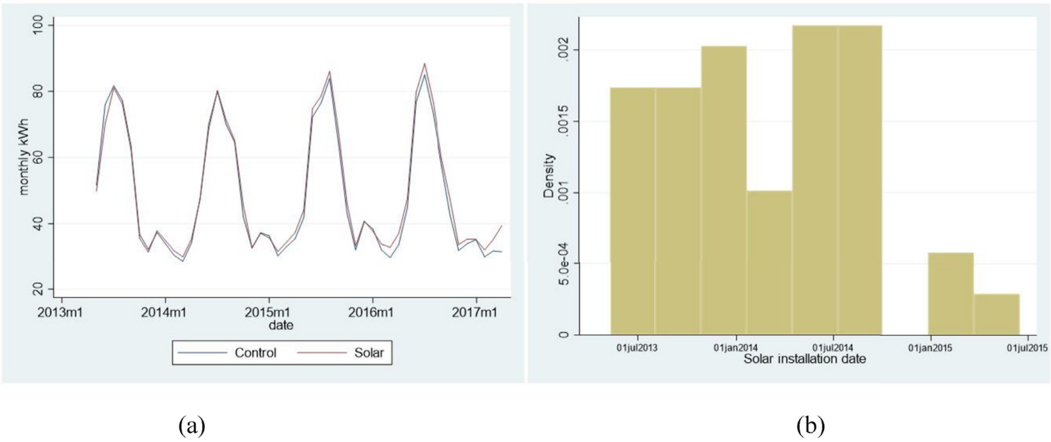


Fig. A7. Monthly average electricity consumption for the control and treatment group and the installation dates for the treatment group; using only solar customers with both pre- and post-installation energy consumption data.

Table A1
Balancing check for propensity score matching results

Variable	Unmatched/Matched	Mean			%reduction |bias|	t-test		V(T)/V(C) [a]
		Treated	Control	%bias		t	p>|t|	
TOU pricing	U	0.50	0.38	22.8		3.48	0.001	.
	M	0.50	0.48	3.3	85.4	0.36	0.718	.
Owner occupied	U	0.92	0.71	56.7		7.18	0	.
	M	0.92	0.91	3.3	94.2	0.49	0.625	.
Household income	U	72.92	58.24	33.6		5.16	0	1.09
	M	72.92	74.59	−3.8	88.6	−0.41	0.682	0.98
Square footage	U	2.08	1.62	58.5		8.42	0	0.8
	M	2.08	2.08	−0.4	99.3	−0.05	0.962	1.18
# of persons in the household	U	2.49	2.21	23.5		3.72	0	1.24
	M	2.49	2.37	10.4	56	1.12	0.264	1.12
Household head being white	U	0.77	0.77	0.9		0.14	0.887	.
	M	0.77	0.77	1	−3.4	0.11	0.914	.
# of stories	U	1.20	1.22	−4.8		−0.69	0.489	0.79
	M	1.20	1.23	−8.5	−76.1	−0.9	0.37	0.68
Vintage of house	U	30.35	28.70	9.7		1.34	0.179	0.66
	M	30.35	31.72	−8.1	16.5	−0.94	0.347	0.79
Household head age	U	56.55	56.56	−0.1		−0.02	0.986	0.87
	M	56.55	56.48	0.4	−229.6	0.05	0.963	1.05
Primary residence	U	0.95	0.93	6.9		0.99	0.323	.
	M	0.95	0.96	−3.5	49.1	−0.44	0.663	.

(*continued on next page*)

Table A1 (*continued*)

Variable	Unmatched/Matched	Mean		%bias	%reduction |bias|	t-test		V(T)/V(C) [a]
		Treated	Control			t	p>|t|	
Swimming pool	U	0.44	0.26	38.8		6.2	0	.
	M	0.44	0.49	−11.4	70.7	−1.18	0.239	.
Programmable thermostats	U	0.75	0.58	34.7		4.97	0	.
	M	0.75	0.77	−5.3	84.8	−0.63	0.527	.
Single family house	U	0.98	0.77	69.7		8.01	0	.
	M	0.98	0.99	−2.6	96.2	−0.82	0.412	.

[a] Variance ratio.

Table A2
Balancing check for coarsened exact matching results

Solar customer						Balancing check	
Variable	Obs	Mean	Std. Dev.	Min	Max	SMD	VR
Owner occupied	116	0.97	0.18	0	1	0.10	1.87
TOU pricing	116	0.53	0.50	0	1	0.13	1.00
Household income	116	70.34	37.37	3.75	150	0.10	1.06
Square footage	116	2.04	0.59	0.75	3	0.08	0.99
Number of persons in the household	116	2.13	1.09	1.5	5	0.23	1.51
Household head being white	113	0.89	0.31	0	1	0.22	2.10
Number of stories	114	1.12	0.33	1	2	0.18	1.67
Vintage of the house in years	116	27.93	18.79	7.5	50	0.16	1.09
Age of household head	116	58.53	12.60	25	75	0.29	1.43
Primary residence	116	0.96	0.20	0	1	0.12	1.94
Having a swimming pool	116	0.42	0.50	0	1	0.13	1.06
Single family house	115	1	0	1	1	N∖A	N∖A
Having programmable thermostats	116	0.79	0.41	0	1	0.10	0.89
Non-solar customer							
Variable	Obs	Mean	Std. Dev.	Min	Max		
Owner occupied	275	0.98	0.13	0	1		
TOU pricing	275	0.47	0.50	0	1		
Household income	275	66.55	36.37	3.75	150		
Square footage	275	1.99	0.59	0.75	3		
Number of persons in the household	275	1.89	0.89	1.5	5		
Household head being white	273	0.95	0.21	0	1		
Number of stories	273	1.07	0.25	1	2		
Vintage of the house in years	275	30.87	18.00	7.5	50		
Age of household head	275	61.87	10.52	25	75		
Primary residence	275	0.98	0.15	0	1		
Having a swimming pool	275	0.36	0.48	0	1		
Single family house	274	1	0	1	1		
Having programmable thermostats	275	0.75	0.43	0	1		

Table A3
Monthly level analysis to examine the impact of solar electricity generation on monthly electricity consumption

PSM sample; All rate plans; Using all time periods for both control and treatment groups	
Solar electricity	0.144***
	(0.035)
Price	−2405.203**
	(1090.435)
Constant	1172.067***
	(79.121)
CDD	Yes
HDD	Yes
Fixed effects	
Account	Yes
Year of sample	Yes
Month of year	Yes
N	21,478

Table A4
Results using other forms to control for CDD and HDD (with propensity score matching)

	Percentile spline	Cubic equation
Solar electricity	0.183***	0.182***
	(0.035)	(0.035)
Price	−60.945**	−60.646**
	(25.034)	(25.033)
Holiday	0.522*	0.543*
	(0.314)	(0.314)
Constant	38.372***	38.624***
	(1.722)	(1.722)
CDD	Percentile spline	Cubic equation
HDD	Percentile spline	Cubic equation
Fixed effects		
Account year	Yes	Yes
Month of year	Yes	Yes
Day of month	Yes	Yes
Day of week	Yes	Yes
N	619,788	619,788

Table A5
Impact of solar electricity generation on daily electricity consumption

	all rate	
	PSM	CEM
Solar Electricity*MONTH1	0.061	0.094
	(0.055)	(0.084)
Solar Electricity*MONTH2	0.088**	0.102*
	(0.044)	(0.054)
Solar Electricity*MONTH3	0.105***	0.089*
	(0.038)	(0.046)
Solar Electricity*MONTH4	0.129***	0.117***
	(0.036)	(0.041)
Solar Electricity*MONTH5	0.136***	0.133***
	(0.033)	(0.045)
Solar Electricity*MONTH6	0.211***	0.209***
	(0.044)	(0.075)
Solar Electricity*MONTH7	0.181***	0.155**
	(0.046)	(0.077)
Solar Electricity*MONTH8	0.220***	0.199***
	(0.045)	(0.076)
Solar Electricity*MONTH9	0.208***	0.201***
	(0.040)	(0.066)
Solar Electricity*MONTH10	0.206***	0.205***
	(0.036)	(0.050)
Solar Electricity*MONTH11	0.108**	0.118*
	(0.047)	(0.061)
Solar Electricity*MONTH12	0.041	0.075
	(0.058)	(0.088)
Average daily electricity price	−55.807**	−72.811**
	(24.937)	(33.663)
Holiday	0.977***	0.832**
	(0.285)	(0.382)
Constant	39.489***	36.759***
	(1.758)	(2.495)
CDD	Yes	Yes
HDD	Yes	Yes
Fixed effects		
Account year	Yes	Yes
Month of year	Yes	Yes
Day of month	Yes	Yes

(*continued on next page*)

Table A5 (*continued*)

	all rate	
	PSM	CEM
Day of week	Yes	Yes
N	619,788	504,795

Table A6
Analysis using only solar customers with both pre- and post-installation energy consumption data

Model number	Estimating response to solar electricity generation	Checking pre-installation energy trend	
	1	2	
Solar Electricity	0.146**	SOLAR	−0.170
	(0.06)		(0.279)
Average daily electricity price	−96.710**	Average daily electricity price	−355.149***
	(45.444)		(12.557)
Constant	42.018***	Constant	61.947***
	(2.878)		(1.642)
CDD	Yes	CDD	Yes
HDD	Yes	HDD	Yes
Fixed effects		Control	
Account year	Yes	Year of sample	Yes
Month of year	Yes	Month of year	Yes
Day of month	Yes	Day of month	Yes
Day of week	Yes	Day of week	Yes
N	182,706	N	47,192

Table A7
Robustness checks

	No price		Price*TOU		Solar electricity*TOU	Machine learning			Solar irradiance check using non-solar consumers only	
	PSM	CEM	PSM	CEM	PSM	CART	LASSO	Ridge	PSM	PSM
Solar electricity	0.186***	0.176***	0.181***	0.169***	0.191**	0.184***	0.161***	0.162***		
	(0.036)	(0.059)	(0.035)	(0.058)	(0.077)	(0.033)	(0.041)	(0.041)		
Solar electricity*TOU					−0.099					
					(0.070)					
Solar irradiance (DNI)									0.001	
									(0.001)	
Hypothetical solar electricity										0.032
										(0.022)
Electricity price			−94.492**	−109.124**	−57.117**	−52.393***			−88.253**	−89.793**
			(38.799)	(54.832)	(24.589)	(16.746)			(35.086)	(44.851)
Price*TOU			88.865**	82.802						
			(38.468)	(52.908)						
Holiday	0.975***	1.142***	0.904***	0.933**	0.593*	0.507*			0.555**	0.662***
	(0.248)	(0.350)	(0.266)	(0.369)	(0.310)	(0.270)			(0.229)	(0.198)
Constant	34.894***	31.547***	38.622***	36.206***	38.793***	38.448***			39.774***	36.191***
	(0.524)	(0.642)	(1.619)	(2.227)	(1.705)	(1.122)			(2.515)	(3.351)
CDD	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
HDD	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Fixed effects										
Account year	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Month of year	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Day of month	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Day of week	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
N	619,788	504,795	619,788	504,795	619,788	4,308,092	5,414,752	5,414,752	368,842	321,361

Table A8
Balancing check for machine learning CART-based matching (using ks stopping rule)

	Treatment		Control		std.eff.sz	stat	p	ks	ks.pval
	Mean	Std. Dev.	Mean	Std. Dev.					
TOU pricing	0.496	0.501	0.504	0.5	−0.015	−0.224	0.823	0.008	1
Owner occupied	0.922	0.269	0.917	0.276	0.02	0.3	0.764	0.005	1
Household income	72.92	44.653	73.051	44.549	−0.003	−0.042	0.966	0.005	1
Square footage	2.078	0.731	2.07	0.719	0.011	0.156	0.876	0.015	1
Number of persons in the household	2.492	1.268	2.482	1.258	0.008	0.115	0.909	0.004	1
Household head being white	0.775	0.419	0.779	0.415	−0.01	−0.151	0.88	0.004	1
Number of stories	1.197	0.409	1.195	0.406	0.005	0.071	0.944	0.002	1
Vintage of the house in years	30.348	15.119	30.242	15.149	0.007	0.102	0.918	0.009	1
Age of household head	56.545	14.657	56.641	14.611	−0.007	−0.094	0.925	0.008	1
Primary residence	0.951	0.217	0.953	0.211	−0.012	−0.18	0.857	0.003	1
Having a swimming pool	0.439	0.497	0.436	0.496	0.006	0.087	0.931	0.003	1
Having programmable thermostats	0.746	0.436	0.74	0.438	0.012	0.184	0.854	0.005	1
Single family house	0.004	0.064	0.004	0.066	−0.004	−0.057	0.955	0	1

Table A9
Regression results for the impact of solar panel adoption on hourly delivered electricity

	Summer		Winter	
	PSM	CEM	PSM	CEM
Solar*Hour1	−0.020	−0.263*	−0.240***	−0.324***
	(0.093)	(0.134)	(0.069)	(0.083)
Solar*Hour2	−0.027	−0.256*	−0.263***	−0.341***
	(0.095)	(0.135)	(0.070)	(0.086)
Solar*Hour3	−0.055	−0.254*	−0.272***	−0.330***
	(0.096)	(0.138)	(0.070)	(0.084)
Solar*Hour4	−0.038	−0.164	−0.270***	−0.300***
	(0.096)	(0.138)	(0.071)	(0.088)
Solar*Hour5	−0.008	−0.023	−0.259***	−0.190**
	(0.097)	(0.140)	(0.071)	(0.088)
Solar*Hour6	−0.034	−0.014	−0.278***	−0.139
	(0.095)	(0.137)	(0.071)	(0.094)
Solar*Hour7	−0.216**	−0.133	−0.283***	−0.068
	(0.095)	(0.137)	(0.074)	(0.099)
Solar*Hour8	−0.586***	−0.452***	−0.370***	−0.133
	(0.100)	(0.144)	(0.067)	(0.098)
Solar*Hour9	−1.011***	−0.880***	−0.725***	−0.479***
	(0.101)	(0.143)	(0.068)	(0.080)
Solar*Hour10	−1.366***	−1.246***	−0.999***	−0.794***
	(0.102)	(0.141)	(0.072)	(0.076)
Solar*Hour11	−1.673***	−1.557***	−1.146***	−0.981***
	(0.103)	(0.145)	(0.073)	(0.082)
Solar*Hour12	−1.926***	−1.800***	−1.190***	−1.031***
	(0.105)	(0.150)	(0.074)	(0.086)
Solar*Hour13	−2.126***	−1.964***	−1.193***	−1.015***
	(0.107)	(0.154)	(0.074)	(0.084)
Solar*Hour14	−2.225***	−2.040***	−1.159***	−0.979***
	(0.105)	(0.147)	(0.072)	(0.080)
Solar*Hour15	−2.217***	−2.068***	−1.095***	−0.933***
	(0.106)	(0.144)	(0.070)	(0.080)
Solar*Hour16	−2.049***	−1.925***	−0.996***	−0.836***
	(0.103)	(0.136)	(0.066)	(0.077)
Solar*Hour17	−1.573***	−1.535***	−0.805***	−0.667***
	(0.101)	(0.128)	(0.060)	(0.069)
Solar*Hour18	−0.855***	−0.884***	−0.447***	−0.372***
	(0.101)	(0.128)	(0.060)	(0.067)
Solar*Hour19	−0.234**	−0.321**	−0.213***	−0.168**
	(0.101)	(0.125)	(0.063)	(0.075)
Solar*Hour20	−0.003	−0.069	−0.187***	−0.108
	(0.097)	(0.126)	(0.064)	(0.078)

(*continued on next page*)

Table A9 (*continued*)

	Summer		Winter	
	PSM	CEM	PSM	CEM
Solar*Hour21	−0.017	−0.129	−0.183***	−0.124
	(0.095)	(0.131)	(0.062)	(0.077)
Solar*Hour22	−0.026	−0.217*	−0.206***	−0.184**
	(0.092)	(0.123)	(0.064)	(0.075)
Solar*Hour23	−0.008	−0.262*	−0.245***	−0.279***
	(0.094)	(0.134)	(0.066)	(0.081)
Solar*Hour24	−0.026	−0.283**	−0.245***	−0.308***
	(0.092)	(0.132)	(0.066)	(0.079)
Marginal electricity price	−3.317***	−4.103***	−4.969***	−6.440***
	(0.370)	(0.468)	(0.863)	(1.171)
Holiday	0.003	−0.001	0.044***	0.039***
	(0.010)	(0.012)	(0.006)	(0.007)
Constant	1.058***	1.121***	1.556***	1.606***
	(0.073)	(0.082)	(0.075)	(0.108)
CDD	Yes	Yes	Yes	Yes
HDD	Yes	Yes	Yes	Yes
Fixed effects				
Account-year	Yes	Yes	Yes	Yes
Month of year	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes
Hour of day	Yes	Yes	Yes	Yes
N	7,856,493	4,661,933	7,588,691	4,500,138

Clustered standard errors in parentheses; *p < 0.1 **p < 0.05 ***p < 0.01.

Table A10
Environmental impact evaluation with rebound effects

Hour	Estimated coefficient for solar panel (delta kWh per hour)	Marginal damages for emissions [a]				Annual savings from reduced emissions by a typical solar panel system by hour			
		CO_2 ($/kWh)	SO_2($/kWh)	NO_X($/kWh)	PM[b] ($/kWh)	CO_2 ($)	SO_2($)	NO_X($)	PM ($)
1	−0.183	0.0204	0.0055	0.0021	0.0007	−1.36	−0.37	−0.14	−0.05
2	−0.196	0.021	0.0054	0.0021	0.0009	−1.50	−0.39	−0.15	−0.06
3	−0.215	0.0183	0.0049	0.002	0.0005	−1.44	−0.38	−0.16	−0.04
4	−0.205	0.0208	0.0052	0.0022	0.0007	−1.56	−0.39	−0.16	−0.05
5	−0.183	0.0207	0.0049	0.0021	0.0009	−1.38	−0.33	−0.14	−0.06
6	−0.203	0.0176	0.0038	0.0018	0.0008	−1.30	−0.28	−0.13	−0.06
7	−0.291	0.0148	0.0035	0.0016	0.0004	−1.57	−0.37	−0.17	−0.04
8	−0.515	0.0153	0.0034	0.0015	0.0005	−2.88	−0.64	−0.28	−0.09
9	−0.904	0.0153	0.0036	0.0014	0.0005	−5.05	−1.19	−0.46	−0.16
10	−1.22	0.0151	0.0034	0.0014	0.0004	−6.72	−1.51	−0.62	−0.18
11	−1.45	0.0149	0.003	0.0013	0.0004	−7.89	−1.59	−0.69	−0.21
12	−1.603	0.0148	0.0029	0.0013	0.0004	−8.66	−1.70	−0.76	−0.23
13	−1.709	0.0142	0.0027	0.0013	0.0003	−8.86	−1.68	−0.81	−0.19
14	−1.742	0.014	0.0026	0.0013	0.0003	−8.90	−1.65	−0.83	−0.19
15	−1.716	0.014	0.0024	0.0013	0.0003	−8.77	−1.50	−0.81	−0.19
16	−1.594	0.0139	0.0025	0.0013	0.0003	−8.09	−1.45	−0.76	−0.17
17	−1.265	0.0136	0.0026	0.0013	0.0004	−6.28	−1.20	−0.60	−0.18
18	−0.725	0.0133	0.0024	0.0012	0.0003	−3.52	−0.64	−0.32	−0.08
19	−0.289	0.0132	0.0025	0.0012	0.0002	−1.39	−0.26	−0.13	−0.02
20	−0.158	0.014	0.0026	0.0013	0.0003	−0.81	−0.15	−0.07	−0.02
21	−0.162	0.0149	0.0032	0.0014	0.0004	−0.88	−0.19	−0.08	−0.02
22	−0.178	0.0167	0.0039	0.0015	0.0005	−1.08	−0.25	−0.10	−0.03
23	−0.185	0.0181	0.0045	0.0017	0.0006	−1.22	−0.30	−0.11	−0.04
24	−0.191	0.0198	0.0051	0.002	0.0007	−1.38	−0.36	−0.14	−0.05
Total									$122.34/ year

Notes.
[a] The average annual marginal damages for emissions in WECC are obtained from (Holland et al., 2016).
[b] PM: particulate matter.

Table A11
Environmental impact evaluation without rebound effects using solar electricity generation as the reduction of grid-based electricity consumption

Hour	Negative of average hourly solar electricity (kWh/hr)	Marginal damages for emissions [a]				Annual savings from reduced emissions by a typical solar panel system by hour			
		CO_2 ($/kWh)	SO_2($/kWh)	NO_X($/kWh)	PM[b] ($/kWh)	CO_2 ($)	SO_2($)	NO_X($)	PM ($)
1	0.000	0.0204	0.0055	0.0021	0.0007	0.00	0.00	0.00	0.00
2	0.000	0.021	0.0054	0.0021	0.0009	0.00	0.00	0.00	0.00
3	0.000	0.0183	0.0049	0.002	0.0005	0.00	0.00	0.00	0.00
4	0.000	0.0208	0.0052	0.0022	0.0007	0.00	0.00	0.00	0.00
5	0.000	0.0207	0.0049	0.0021	0.0009	0.00	0.00	0.00	0.00
6	−0.006	0.0176	0.0038	0.0018	0.0008	−0.04	−0.01	0.00	0.00
7	−0.124	0.0148	0.0035	0.0016	0.0004	−0.67	−0.16	−0.07	−0.02
8	−0.572	0.0153	0.0034	0.0015	0.0005	−3.20	−0.71	−0.31	−0.10
9	−1.376	0.0153	0.0036	0.0014	0.0005	−7.68	−1.81	−0.70	−0.25
10	−2.188	0.0151	0.0034	0.0014	0.0004	−12.06	−2.71	−1.12	−0.32
11	−2.794	0.0149	0.003	0.0013	0.0004	−15.20	−3.06	−1.33	−0.41
12	−3.154	0.0148	0.0029	0.0013	0.0004	−17.04	−3.34	−1.50	−0.46
13	−3.262	0.0142	0.0027	0.0013	0.0003	−16.91	−3.22	−1.55	−0.36
14	−3.124	0.014	0.0026	0.0013	0.0003	−15.96	−2.96	−1.48	−0.34
15	−2.746	0.014	0.0024	0.0013	0.0003	−14.03	−2.41	−1.30	−0.30
16	−2.121	0.0139	0.0025	0.0013	0.0003	−10.76	−1.94	−1.01	−0.23
17	−1.315	0.0136	0.0026	0.0013	0.0004	−6.53	−1.25	−0.62	−0.19
18	−0.542	0.0133	0.0024	0.0012	0.0003	−2.63	−0.48	−0.24	−0.06
19	−0.120	0.0132	0.0025	0.0012	0.0002	−0.58	−0.11	−0.05	−0.01
20	−0.006	0.014	0.0026	0.0013	0.0003	−0.03	−0.01	0.00	0.00
21	0.000	0.0149	0.0032	0.0014	0.0004	0.00	0.00	0.00	0.00
22	0.000	0.0167	0.0039	0.0015	0.0005	0.00	0.00	0.00	0.00
23	0.000	0.0181	0.0045	0.0017	0.0006	0.00	0.00	0.00	0.00
24	0.000	0.0198	0.0051	0.002	0.0007	0.00	0.00	0.00	0.00
Total									$161.83/year

Notes.
[a] The average annual marginal damages for emissions in WECC are obtained from (Holland et al., 2016).
[b] PM: particulate matter.

Appendix B. Results of other model specifications

Impact on hourly electricity delivered from an additional 1 kW system

In order to examine the impact from an additional 1 kW (AC) solar installation on hourly electricity delivered to the customer, we run the following regression:

$$\text{kWh}_{ich} = \alpha_{iy} + \sum_{H=1}^{24} \beta_H^{AC} \textit{Solar panel}_{ih} {*} \textit{KWAC}_{ih} {*} I_H + \gamma p_{ih} + f(HDD_{ih})\boldsymbol{\theta} + f(CDD_{ih})\boldsymbol{\eta} + \delta \textit{Holiday}_d + \textit{Hour of day}$$
$$+ \textit{Day of month} + \textit{Day of week} + \textit{month of year} + \textit{year of sample} + \varepsilon_{ih}$$

where $KWAC_{ih}$ is the size of solar panel system with the unit kW. β_H^{AC} measures the impact of additional 1 kW (AC) of solar panel system for each hour of day. This regression model looks at the impact of an additional kW solar system on hourly electricity needed from the grid. Figure B1 shows the results of the coefficients that measure the change in hourly kWh due to an additional 1 kW solar panel system. Detailed regression results are listed in Table B1. We only run the equation on the matched sample using propensity score matching and for all rates. Figure B1 shows similar results compared to Fig. 6. The magnitude of hourly kWh reduction is smaller, given that it is now only the reduction from an additional 1 kW system, whereas on average the size of solar panel systems in our dataset is 6.6 kW (AC). During the summer, the maximum reduction is −0.32 kWh/hr/kWAC. If we multiply this by the average system size (0.32*6.6 = 2.1), we obtain similar results compared to 2.2 kWh/hr from directly examining the solar panel system adoption in Fig. 6.

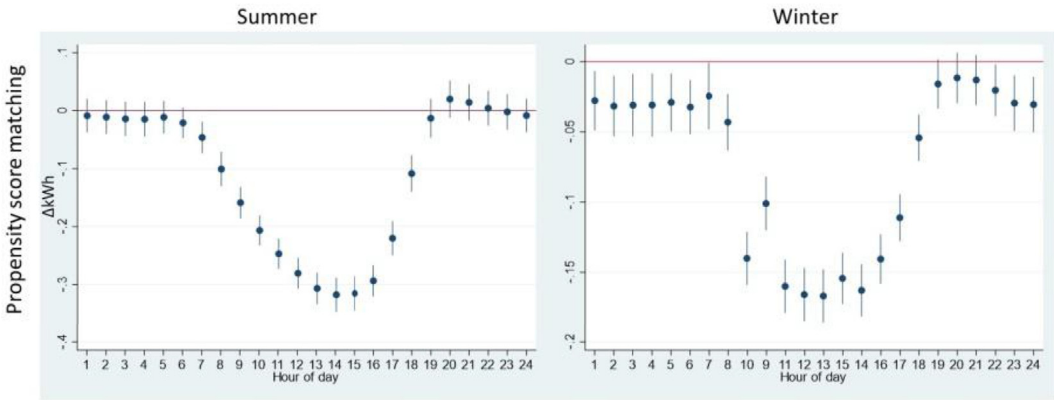


Fig. B1. Impact of an additional 1 kW solar system on hourly electricity delivered from the grid. Notes: Blue dots indicate the value of coefficients for *Solar panel adoption*kW* for that hour; Vertical blue lines indicate 95% confidence intervals.

Table B1
Impact of 1 additional kW system size on hourly delivered electricity

All rate plans	Summer	Winter
Solar*Hour*kWAC1	−0.009	−0.028***
	(0.015)	(0.011)
Solar*Hour*kWAC2	−0.011	−0.032***
	(0.015)	(0.011)
Solar*Hour*kWAC3	−0.014	−0.031***
	(0.015)	(0.011)
Solar*Hour*kWAC4	−0.015	−0.031***
	(0.015)	(0.011)
Solar*Hour*kWAC5	−0.011	−0.029***
	(0.014)	(0.010)
Solar*Hour*kWAC6	−0.021	−0.032***
	(0.013)	(0.010)
Solar*Hour*kWAC7	−0.046***	−0.024**
	(0.014)	(0.012)
Solar*Hour*kWAC8	−0.101***	−0.043***
	(0.015)	(0.010)
Solar*Hour*kWAC9	−0.159***	−0.140***
	(0.014)	(0.010)
Solar*Hour*kWAC10	−0.206***	−0.101***
	(0.013)	(0.010)
Solar*Hour*kWAC11	−0.247***	−0.160***
	(0.013)	(0.010)
Solar*Hour*kWAC12	−0.280***	−0.166***
	(0.013)	(0.010)
Solar*Hour*kWAC13	−0.307***	−0.167***
	(0.014)	(0.010)
Solar*Hour*kWAC14	−0.317***	−0.154***
	(0.015)	(0.009)
Solar*Hour*kWAC15	−0.315***	−0.163***
	(0.015)	(0.009)
Solar*Hour*kWAC16	−0.293***	−0.141***
	(0.014)	(0.009)
Solar*Hour*kWAC17	−0.220***	−0.111***
	(0.015)	(0.008)
Solar*Hour*kWAC18	−0.108***	−0.054***
	(0.016)	(0.008)
Solar*Hour*kWAC19	−0.013	−0.016*
	(0.017)	(0.009)
Solar*Hour*kWAC20	0.020	−0.012
	(0.016)	(0.009)
Solar*Hour*kWAC21	0.014	−0.013

Table B1 (*continued*)

All rate plans	Summer	Winter
	(0.016)	(0.009)
Solar*Hour*kWAC22	0.004	−0.020**
	(0.015)	(0.009)
Solar*Hour*kWAC23	−0.002	−0.030***
	(0.015)	(0.010)
Solar*Hour*kWAC24	−0.008	−0.031***
	(0.015)	(0.010)
Marginal electricity price	−3.400***	−4.717***
	(0.368)	(0.842)
Holiday	0.003	−0.025***
	(0.010)	(0.006)
Constant	1.080***	0.100***
	(0.073)	(0.019)
CDD	Yes	Yes
HDD	Yes	Yes
Fixed effects		
Account year	Yes	Yes
Month of year	Yes	Yes
Day of week	Yes	Yes
Hour of day	Yes	Yes
N	7,856,493	7,588,691

Clustered standard errors in parentheses; *p < 0.1 **p < 0.05 ***p < 0.01.

Impact on daily net purchase from the grid

Here we analyze the impact of solar adoption on net electricity purchase from the grid kWh_d, which is electricity delivered from the grid minus the electricity sold by the customer to the grid. We do this analysis at the daily level using register read meter data. The reduction in net purchase is after rebound effects, meaning that it reflects not only the amount of electricity generated by solar panels, but also the change in customer electricity consumption behavior, such as rebound effects and load-shifting behaviors. We run the following panel regression:

$$\text{kWh}_{id} = \alpha_{iy} + \sum_{M=1}^{12} \beta_M \mathit{Solar\ panel}_{id} {*} I_M + \gamma p_{id} + f(\mathit{HDD}_{id})\boldsymbol{\theta} + f(\mathit{CDD}_{id})\boldsymbol{\eta} + \delta \mathit{Holiday}_d + \mathit{Day\ of\ month} + \mathit{Day\ of\ week} + \mathit{month\ of\ year} + \varepsilon_{id}$$

where M indicates month of year; d indicates day of sample; I_M is an indicator variable for each month of year. The coefficients of β_M measure the impact by month and are illustrated in Figure B2. Results of all coefficients for the regressions are listed in Table B2 in the Appendix. Again PSM and CEM generate similar results while we focus our discussion on PSM. The impact on net electricity purchase is statistically significant in all months, ranging from −26 to −42 kWh/day. The largest reduction in net purchase happens in May.

In order to examine the impact on electricity consumption from an additional 1 kW (AC) solar installation, we run the following regression:

$$\text{kWh}_{id} = \alpha_{iy} + \beta^{AC} \mathit{Solar\ panel}_{id} {*} \mathit{KWAC}_{id} + \gamma p_{id} + f(\mathit{HDD}_{id})\boldsymbol{\theta} + f(\mathit{CDD}_{id})\boldsymbol{\eta} + \delta \mathit{Holiday}_d + \mathit{Day\ of\ month} + \mathit{Day\ of\ week} + \mathit{month\ of\ year} + \varepsilon_{id}$$

where $KWAC_{id}$ is the size of solar panel system with the unit kW. β^{AC} measures the impact of an additional 1 kW (AC) of solar panel system. Results are listed in Table B3 in the Appendix. In the summer, 1 additional kW can reduce daily net electricity purchase by about 4.9 kWh; in winter months, that reduction is 3.9 kWh per day.

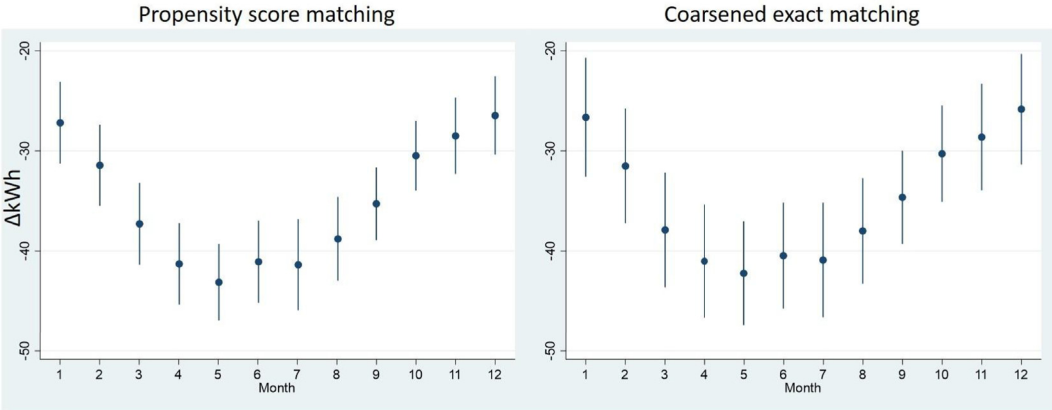


Fig. B2. Impact of solar panel adoption on daily net electricity purchased from the grid. Notes: Blue dots indicate the value of coefficients for *Solar panel adoption* for that month; Vertical blue lines indicate 95% confidence intervals.

Table B2
Impact of solar adoption on daily net electricity purchase from the grid

	All rate	
	CEM	PSM
Solar*Month1	−26.643***	−27.190***
	(3.024)	(2.077)
Solar*Month2	−31.515***	−31.441***
	(2.917)	(2.068)
Solar*Month3	−37.896***	−37.292***
	(2.915)	(2.080)
Solar*Month4	−41.024***	−41.292***
	(2.873)	(2.070)
Solar*Month5	−42.234***	−43.129***
	(2.638)	(1.944)
Solar*Month6	−40.470***	−41.076***
	(2.686)	(2.092)
Solar*Month7	−40.907***	−41.379***
	(2.913)	(2.319)
Solar*Month8	−37.993***	−38.794***
	(2.679)	(2.126)
Solar*Month9	−34.645***	−35.289***
	(2.367)	(1.848)
Solar*Month10	−30.284***	−30.483***
	(2.442)	(1.773)
Solar*Month11	−28.624***	−28.505***
	(2.702)	(1.938)
Solar*Month12	−25.838***	−26.468***
	(2.809)	(1.992)
Average daily electricity price	−75.382**	−61.618**
	(33.158)	(24.676)
Holiday	0.276	0.322
	(0.364)	(0.273)
Constant	38.691***	42.493***
	(2.524)	(1.816)
CDD	Yes	Yes
HDD	Yes	Yes
Fixed effects		
Account year	Yes	Yes
Month of year	Yes	Yes
Day of month	Yes	Yes
Day of week	Yes	Yes
N	504,795	619,788

Clustered standard errors in parentheses; *p < 0.1 **p < 0.05 ***p < 0.01.

Table B3
Impact of 1 additional kW solar panel system on daily net electricity purchase from the grid

	all months	summer	winter
Solar * kWAC	−4.505***	−4.881***	−3.949***
	(0.245)	(0.411)	(0.286)
Average daily electricity price	−43.538*	−42.001***	−127.957***
	(25.287)	(12.011)	(32.574)
Holiday	2.408***	1.650***	2.341***
	(0.323)	(0.401)	(0.266)
Constant	41.460***	41.361***	46.006***
	(1.805)	(1.648)	(2.537)
CDD	Yes	Yes	Yes
HDD	Yes	Yes	Yes
Fixed effects			
Account year	Yes	Yes	Yes
Month of year	Yes	Yes	Yes
Day of month	Yes	Yes	Yes
Day of week	Yes	Yes	Yes
N	619,788	313,821	305,967

Clustered standard errors in parentheses; *$p < 0.1$ **$p < 0.05$ ***$p < 0.01$.

Impact by leasing or owning of the solar panels

We have the information on whether a solar panel system is leased or owned by the adopter. Theoretically, leasing or owning should not influence the impact of solar adoption on consumption behavior. We run the regression models adding interaction terms between solar variable and leasing/own variable. Results are listed in Table B4. We are interested in financial gain from leasing or owning panels, so we focus on the impact on net electricity purchase. When not controlling for system size, panel systems that are leased can reduce a larger amount of net electricity purchase. However, after controlling for system size, leasing and owning do not show a statistically significant difference. This is because leasing is associated with a larger size of panel system as shown in Figure B3.

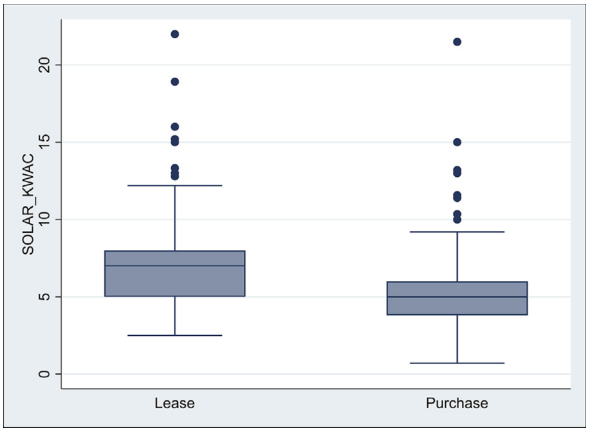


Fig. B3. Solar panel sizes by financing mode.

Impact by cost of panel

If higher per kW panel cost is associated with higher quality (thus higher efficiency) of solar panels, then we might expect a higher impact from an additional 1 kW solar installation for higher-cost panels. To test this empirically, we run regression model with interaction terms between cost of panel, solar panel installation, and size of solar panels. Results are listed in Table B4 and confirm our hypothesis. It shows that higher per kW cost is associated with larger reduction in net electricity purchase.

Impact by household attributes

To analyze how the solar-panel's impacts on electricity consumption Change with respect to household attributes, we add interaction terms between solar electricity generation and attributes in regression models. Results are listed in Table B5. The coefficients of the interaction terms are positive for household income, number of persons in a household, square footage, and owner occupied home, indicating that these types of households increase more of their electricity consumption in response to 1 kWh additional solar electricity generation. For homes with older household heads, the increase in electricity consumption in response to solar electricity generation is less than those with younger heads.

Table B4
Analysis of financing mode, panel cost, and environmental ideology

Financing mode				Cost		Environmental ideology	
Dependent variable	Daily net electricity purchase from the grid			Daily net electricity purchase from the grid		Daily gross consumption	
SOLAR [a]	−18.363***	SOLAR *kWAC	−4.094***	SOLAR *kWAC	−3.207***	SOLAR	6.982
	(2.859)		(0.736)		(0.892)		(4.383)
SOLAR* LEASE	−20.885***	SOLAR*kWAC *LEASE	−0.798	SOLAR *kWAC*COST	−0.340*	SOLAR* LIBERAL	−21.578*
	(3.701)		(0.778)		(0.187)		(11.279)
Average daily electricity price	−24.159	Average daily electricity price	−24.075	Average daily electricity price	−8.066	Average daily electricity price	−44.655**
	(22.436)		(22.457)		(33.12)		(18.729)
Holiday	1.277***	Holiday	1.244**	Holiday	1.477***	Holiday	0.736
	(0.472)		(0.478)		(0.328)		(0.487)
Constant	48.647***	Constant	46.100***	Constant	45.364***	Constant	42.055***
	(1.993)		(1.944)		(2.561)		(1.271)
CDD	Yes	CDD	Yes	CDD	Yes	CDD	Yes
HDD	Yes	HDD	Yes	HDD	Yes	HDD	Yes
Fixed effects							
Account year	Yes	Account year	Yes	Account year	Yes	Account year	Yes
Month of year	Yes	Month of year	Yes	Month of year	Yes	Month of year	Yes
Day of month	Yes	Day of month	Yes	Day of month	Yes	Day of month	Yes
Day of week	Yes	Day of week	Yes	Day of week	Yes	Day of week	Yes
N	119,433	N	119,433	N	119,433	N	269,429

Clustered standard errors in parentheses; *p < 0.1 **p < 0.05 ***p < 0.01.
[a] SOLAR is a dummy variable indicating solar adoption status.

Table B5
Analysis of household attributes

Model number	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Household income	Household age	Number of people in a household	Square footage	Vintage of the house	Owner occupy	Primary residence
Solar Electricity [a]	0.064	0.588***	−0.168**	−0.280***	0.254***	−0.099	−0.095
	(0.064)	(0.152)	(0.075)	(0.100)	(0.071)	(0.158)	(0.423)
Solar Electricity*Attribute	0.002*	−0.007***	0.123***	0.202***	−0.002	0.295*	0.283
	(0.001)	(0.003)	(0.026)	(0.049)	(0.002)	(0.162)	(0.424)
Average daily electricity price	−60.741**	−60.463**	−60.161**	−61.847**	−60.254**	−60.217**	−60.335**
	(24.990)	(24.969)	(24.887)	(24.923)	(25.007)	(25.019)	(25.024)
Holiday	0.565*	0.554*	0.516*	0.532*	0.571*	0.575*	0.559*
	(0.312)	(0.313)	(0.311)	(0.312)	(0.312)	(0.312)	(0.313)
Constant	39.100***	39.098***	39.191***	39.243***	39.016***	39.012***	39.056***
	(1.725)	(1.738)	(1.736)	(1.724)	(1.727)	(1.726)	(1.727)
CDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HDD	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects							
Account year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of month	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	619,788	619,788	619,788	619,788	619,788	619,788	619,788

Clustered standard errors in parentheses; *p < 0.1 **p < 0.05 ***p < 0.01.
[a] Solar Electricity is the daily electricity generated by the solar panels of a household.

References

Azevedo, I.M., 2014. Consumer end-use energy efficiency and rebound effects. Annu. Rev. Environ. Resour. 39, 393–418.
Blackwell, M., Iacus, S.M., King, G., Porro, G., 2009. Cem: coarsened exact matching in Stata. STATA J. 9 (4), 524–546.
Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Mark. Sci. 31 (6), 900–912.
Boomhower, J.P., Davis, L.W., 2017. *Do Energy Efficiency Investments Deliver at the Right Time?* (No. W23097). National Bureau of Economic Research.
Chan, N.W., Gillingham, K., 2015. The microeconomic theory of the rebound effect and its welfare implications. Journal of the Association of Environmental and Resource Economists 2 (1), 133–159.
Costa, D.L., Kahn, M.E., 2013. Energy conservation “nudges” and environmentalist ideology: evidence from a randomized residential electricity field experiment. J. Eur. Econ. Assoc. 11 (3), 680–702.
Cragg, M.I., Zhou, Y., Gurney, K., Kahn, M.E., 2013. Carbon geography: the political economy of congressional support for legislation intended to mitigate greenhouse gas production. Econ. Inq. 51 (2), 1640–1650.
Dastrup, S.R., Zivin, J.G., Costa, D.L., Kahn, M.E., 2012. Understanding the Solar Home price premium: electricity generation and “Green” social status. Eur. Econ. Rev. 56 (5), 961–973.
Deng, G., Newton, P., 2017. Assessing the impact of solar PV on domestic electricity consumption: exploring the prospect of rebound effects. Energy Policy 110, 313–324.
Dominguez, A., Kleissl, J., Luvall, J.C., 2011. Effects of solar photovoltaic panels on roof heat transfer. Sol. Energy 85 (9), 2244–2255.
EIA, 2009. Household energy use in Arizona. Energy Information Administration, report. Available at: https://www.eia.gov/consumption/residential/reports/2009/state_briefs/pdf/az.pdf.
Fowlie, M., Holland, S.P., Mansur, E.T., 2012. What do emissions markets deliver and to whom? Evidence from Southern California's NOx trading program. Am. Econ. Rev. 102 (2), 965–993.
Gillingham, K., Rapson, D., Wagner, G., 2016. The rebound effect and energy efficiency policy. Rev. Environ. Econ. Pol. 10 (1), 68–88.
Gowrisankaran, G., Reynolds, S.S., Samano, M., 2016. Intermittency and the value of renewable energy. J. Political Econ. 124 (4), 1187–1234.
Graziano, M., Gillingham, K., 2014. Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. J. Econ. Geogr. 15 (4), 815–839.
Hledik, R., 2014. Rediscovering residential demand charges. Electr. J. 27 (7), 82–96.
Holland, S.P., Mansur, E.T., Muller, N.Z., Yates, A.J., 2016. Are there environmental benefits from driving electric vehicles? The importance of local factors. Am. Econ. Rev. 106 (12), 3700–3729.
Holland, S.P., Mansur, E.T., Muller, N., Yates, A.J., 2018. Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation (No. W25339). National Bureau of Economic Research.
Ito, K., 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. Am. Econ. Rev. 104 (2), 537–563.
Johnson, E., Beppler, R., Blackburn, C., Staver, B., Brown, M., Matisoff, D., 2017. Peak shifting and cross-class subsidization: the impacts of solar PV on changes in electricity costs. Energy Policy 106, 436–444.
La Nauze, A., 2018. Power from the People: Rooftop Solar and a Downward-Sloping Supply of Electricity.
Lee, B.K., Lessler, J., Stuart, E.A., 2010. Improving propensity score weighting using machine learning. Stat. Med. 29 (3), 337–346.
Leloux, J., Narvarte, L., Trebosc, D., 2012. Review of the performance of residential PV systems in France. Renew. Sustain. Energy Rev. 16 (2), 1369–1376.
Liang, J., Liu, P., Qiu, Y., Wang, Y.D., Xing, B., 2018a. Getting More of Something without Subsidizing it: Impact of Time-Of-Use Electricity Pricing on Residential Energy Efficiency and Solar Panel Adoption. USAEE. Working Paper No. 18-342. https://doi.org/10.2139/ssrn.3180710.
Liang, J., Qiu, Y., James, T., Ruddell, B.L., Dalrymple, M., Earl, S., Castelazo, A., 2018b. Do energy retrofits work? Evidence from commercial and residential buildings in Phoenix. J. Environ. Econ. Manag. 92, 726–743.
Marszal, A.J., Heiselberg, P., Bourrelle, J.S., Musall, E., Voss, K., Sartori, I., Napolitano, A., 2011. Zero Energy Building–A review of definitions and calculation methodologies. Energy Build. 43 (4), 971–979.
Mau, S., Jahn, U., 2006. Performance Analysis of Grid-Connected PV Systems. EUPVSEC, pp. 2676–2680.
McKenna, E., Pless, J., Darby, S.J., 2018. Solar photovoltaic self-consumption in the UK residential sector: new estimates from a smart grid demonstration project. Energy Policy 118, 482–491.
McLaren, J., Davidson, C., Miller, J., Bird, L., 2015. Impact of rate design alternatives on residential solar customer bills: increased fixed charges, minimum bills and demand-based rates. Electr. J. 28 (8), 43–58.
Noll, D., Dawes, C., Rai, V., 2014. Solar community organizations and active peer effects in the adoption of residential PV. Energy Policy 67, 330–343.
Novan, K., Smith, A., 2018. The incentive to overinvest in energy efficiency: evidence from hourly smart-meter data. Journal of the Association of Environmental and Resource Economists 5 (3), 577–605.
Oozeki, T., Yamada, T., Otani, K., Takashima, T., Kato, K., 2010. Performance trends in grid-connected photovoltaic systems for public and industrial use in Japan. Prog. Photovoltaics Res. Appl. 18 (8), 596–602.
Parida, B., Iniyan, S., Goic, R., 2011. A review of solar photovoltaic technologies. Renew. Sustain. Energy Rev. 15 (3), 1625–1636.
Pless, J., McKenna, E., 2018. Solar Endowment Salience and Electricity Consumption Substitution.
Qiu, Y., 2014. Energy efficiency and rebound effects: an econometric analysis of energy demand in the commercial building sector. Environ. Resour. Econ. 59 (2), 295–335.
Qiu, Y., Kahn, M.E., 2018a. Better sustainability assessment of green buildings with high-frequency data. Nature Sustainability 1, 642–649.
Qiu, Y., Kahn, M.E., 2018b. New Estimates of Energy Star Commercial Building Energy Performance.
Qiu, Y., Patwardhan, A., 2018. Big data and residential energy efficiency evaluation. Current Sustainable/Renewable Energy Reports 1–9.
Qiu, Y., Colson, G., Grebitus, C., 2014. Risk preferences and purchase of energy-efficient technologies in the residential sector. Ecol. Econ. 107, 216–229.
Qiu, Y., Wang, Y.D., Wang, J., 2017. Soak up the sun: impact of solar energy systems on residential home values in Arizona. Energy Econ. 66, 328–336.
Reeves, D.C., Rai, V., Margolis, R., 2017. Evolution of consumer information preferences with market maturity in solar PV adoption. Environ. Res. Lett. 12 (7), 074011.
Rubin, D.B., 2001. Using propensity scores to help design observational studies: application to the tobacco litigation. Health Serv. Outcomes Res. Methodol. 2 (3–4), 169–188.
SEIA, 2014. Solar Energy Industries Association. Solar Market Insight Report. https://www.seia.org/research-resources/solar-market-insight-report-2014-q4.
SEIA, 2018. Arizona Solar. Solar Energy Industries Association. https://www.seia.org/state-solar-policy/arizona-solar.
Siler-Evans, K., Azevedo, I.L., Morgan, M.G., 2012. Marginal emissions factors for the US electricity system. Environ. Sci. Technol. 46 (9), 4742–4748.
Stuart, E.A., 2010. Matching methods for causal inference: a review and a look forward. Stat. Sci.: a review journal of the Institute of Mathematical Statistics 25 (1), 1.
Thomas, B.A., Azevedo, I.L., 2013. Estimating direct and indirect rebound effects for US households with input–output analysis Part 1: theoretical framework. Ecol. Econ. 86, 199–210.
Verdolini, E., Galeotti, M., 2011. At home and abroad: an empirical analysis of innovation and diffusion in energy technologies. J. Environ. Econ. Manag. 61 (2), 119–134.