Time-of-Use Electricity Pricing and Residential Low-carbon Energy Technology Adoption

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ABSTRACT

This paper provides the first empirical evidence on the correlation between Time-Of-Use (TOU) electricity pricing and the adoption of energy efficient appliances and solar panels. We use household-level data in Phoenix, Arizona from an appliance saturation survey of about 16,000 customers conducted by a major electric utility. Our empirical results show that TOU consumers are associated with 27% higher likelihood to install solar panels but not more likely to adopt energy-efficient air conditioning based on the propensity score matching and coarsened exact matching methods. The findings highlight that policy makers could combine TOU and solar panels when implementing educational programs or when giving out financial incentives to consumers. Our results imply that TOU is associated with a similar impact of the incentive offered by \$2,070~\$10,472 tax credits or rebates on solar adoption.

Keywords: Time-of-use (TOU) electricity pricing, Solar panels, Energy efficiency

https://doi.org/10.5547/01956574.41.2.jlia

1. INTRODUCTION

Energy efficiency and solar energy are two measures promoted by policy makers to reduce residential fossil fuel energy consumption and the associated greenhouse gas emissions. Not surprisingly, various policies and financial incentives (e.g., tax credits, direct rebates, etc.) exist to encourage the adoption of these technologies. For example, the cost of typical financial incentives (including direct rebates and tax credits) for the adoption of a solar panel system is on the magnitude of \$5,493–\$9,156 (Solar Energy Industries Association, 2014; Hughes and Podolefsky, 2015; Gillingham and Tsvetanov, 2019). However, despite these costly policy instruments, the penetration of energy efficiency and solar energy is still relatively low. Many organizational, behavioral, and market factors have been analyzed in the existing literature to explain the low adoption level. Yet, the impact of one particular factor (electricity rate structure) on energy efficiency investment and solar panel adoption is often overlooked in empirical studies (Novan and Smith, 2018). In this paper, we show empirically that consumers facing Time-of-use pricing (TOU) are positively correlated with the adoption of solar energy, compared to consumers on non-dynamic pricing plans. Our results

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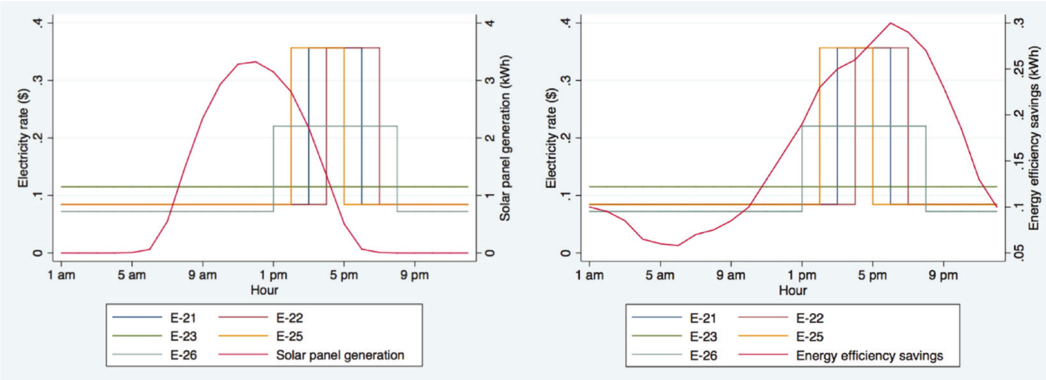
Figure 1: Hourly energy efficiency savings and solar electricity generation



Notes: The left panel is for solar panel electricity generation; the right panel is for energy efficiency savings from efficient ACs. E-21, E-22, E-23, E-25, and E-26 are different price plans as detailed in Table 1. E-23 is a non-dynamic pricing plan while the other plans are TOU plans. The price levels in the figure are prices during July and August. The energy efficiency savings are calculated based on data in July and August. Color figure is available online.

have important implications for policy makers to promote the adoption of solar panels and TOU pricing.

TOU, one of the most widely adopted dynamic pricing programs, charges different electricity prices depending on the time of the day, i.e. higher prices during peak hours (e.g. late afternoon in summer months) and lower prices during non-peak hours. TOU plan provides benefits to the utilities because it helps decrease peak load, which has a higher marginal cost of electricity supply compared to that of the base-load. In addition, reducing peak load helps utilities maintain the grid stability through the reduced likelihood of blackouts during peak hours. TOU can also potentially help the consumers save on energy bills if they switch part of their usage from peak to off-peak hours. This study focuses on another potential positive welfare impact of TOU—its correlation with low-carbon technology adoption, i.e. energy efficiency and solar panel installation.

Figure 1 shows how the price and hour-of-day relationship of typical TOU price plans in Arizona (our study area) corresponds to the timing of electricity savings from solar panels and energy efficiency. The hourly savings from energy efficiency is obtained by recovering the data from Boomhower and Davis (2019), and hourly solar panel electricity generation is obtained by converting hourly solar data from the typical meteorological year (TMY2) dataset using the PVWATTS model (Ong et al., 2010). The figure shows that a significant portion of energy savings happen during peak hours when electricity prices are high. Naturally, this correlation might incentivize consumers to adopt energy efficiency and solar panels if they are on TOU pricing. However, there is little empirical analysis quantifying the correlation between TOU and the adoption of these technologies. This study provides the first empirical evidence of such correlation and fills the gap in existing literature along three dimensions.

First, many studies have shown that the penetration of energy efficiency and solar panels falls short of optimal levels, which is widely referred to as “energy efficiency gap” (Jaffe and Stavins, 1994). Energy efficiency gap is attributed to various organizational, behavioral and market factors (Hirst and Brown, 1990; Weber, 1997; Gillingham et al., 2009; Gillingham and Palmer, 2014; Qiu et al., 2014; Qiu et al., 2017a), such as inefficient pricing of electricity (Gillingham et al., 2009), lack of information (Ramos et al., 2015), and the principal-agent problems (Davis, 2011; Gillingham et al., 2012). Meanwhile, the low adoption of solar energy is also attributed to a range of technical, financial and institutional barriers (Margolis and Zuboy, 2006; Timilsina et al., 2012; Zhang et al., 2012), including high initial cost, technology risk and complexity (Drury et al., 2012), information barriers during information-search process (Rai et al., 2016) and a lack of incentives. However, rate design is often a factor missed in existing empirical studies (Novan and Smith, 2018). This study contributes to this strand of studies by exploring empirically whether rate design is correlated with solar panel and energy efficiency adoption.

Second, there have been many studies focusing on the impacts of TOU rates on energy consumption behaviors and the resulted change in social welfare. Some studies find that consumers shift peak load consumption to off-peak hours (Faruqui and Sergici, 2010; Qiu, et al., 2017a) while others do not find such load shifting behavior (Torriti, 2012; Faruqui et al., 2014). The load shifting behavior could be a result of technology adoption (e.g., demand-side management technology and renewable energy technology), and/or purely shifting energy consuming activities such as watching TV or washing clothes from peak to off-peak hours. This study contributes further to studying the impact of TOU on energy consumption behaviors by examining whether TOU is correlated with energy technology adoption. The adoption of energy efficiency and solar panels can serve as one underlying explanation for the observed load shifting behaviors in existing studies.

Third, despite simulation or systems type of modeling on the impact of rate design on solar panel adoption, there is a lack of empirical evidence for such impacts. Existing simulation studies show that solar adoption should be sensitive to the rate structure (Darghouth et al., 2011; Ong et al., 2012; McLaren et al., 2015; Darghouth et al., 2016). Two seminal empirical studies support that a relationship exists between rate design and adoption of energy efficiency or solar PV. Borenstein (2007 & 2017) show that tariff design provides indirect economic incentives for solar adoption. Specifically, Borenstein (2017) illustrates that the incentive from a tiered tariff is as much as the 30% federal tax credit in California. The calculation also indicates that the lifetime savings could be $7000 more under a tired tariff (increasing block rate) than a flat rate structure. Our empirical results of the correlation between TOU and solar adoption can help verify the simulation studies and further assist policymakers in choosing the appropriate rate designs that better reflect the social cost of providing electricity and potentially encourage the adoption of energy efficiency or solar panels (Ong et al., 2010).

We compare adoption decisions in energy efficient appliances and solar panels between consumers on non-dynamic rates (marginal electricity prices are constant throughout the day) and those on TOU rates. We use household-level data in Phoenix, Arizona from an appliance saturation survey of 16,035 customers conducted by a major electric utility in 2014 for empirical verification. Probit model and statistical matching methods are employed, and robustness checks are conducted using multinomial logit model, bi-variate probit model, and machine learning matching method.

We do not claim that our current finding of the correlation between TOU and technology adoption is causal, although we take steps to try to eliminate confounding factors and endogeneity issues for causal identification. There are two potential threats to causal identification: reverse causality and selection bias. Reverse causality could happen if households first adopt solar panels and then switch to TOU pricing. In our customer level dataset, for all solar customers, only 7 solar customers (less than 1.4% solar customers) switched to TOU after they adopted solar panels. We dropped these 7 solar customers in order to help avoid reverse causality. Also on average solar customers adopted solar panels several years after they enrolled in TOU pricing. In terms of selection bias, since TOU is not mandatory, it is possible that some consumers are more likely to enroll in TOU compared to others while these households are also more likely to adopt energy efficiency and solar panels. If these households have specific characteristics that are not observable to us such as environmental awareness and knowledge on energy usage, a potential self-selection bias exists. We apply a matching approach and include a rich set of covariates to help deal with such selection bias. For a customer that is on TOU pricing, we find a control customer that is similar in terms of home and socio-economic characteristics and that is not on TOU pricing. In addition, we use the adoption of programmable thermostat as a proxy for environmental awareness.

Our empirical evidence suggests that TOU consumers are associated with a 27% higher likelihood to install solar panels, but not more likely to adopt energy efficient AC. Despite our efforts in overcoming the threats to causal identification, due to limitations on non-experimental cross-sectional data, there could still be remaining issues such as other omitted variables that could affect both TOU enrollment and technology adoption. However, even if our empirical finding of the correlation between TOU and solar adoption is not fully causal, quantifying such correlation is still valuable to policy makers. As discussed earlier, both TOU and solar adoption themselves could improve social welfare. TOU is found to enhance social welfare through aligning marginal electricity prices with marginal costs of electricity supply (Qiu et al., 2018; Train and Mehrez,1994). A positive correlation between these two adoptions after controlling for other types of confounding factors implies that if policy makers could encourage these two adoptions together either through informational/educational programs or financial incentives, then consumers could have a higher likelihood of enrolling in TOU or adopting solar compared to just having the policies encouraging TOU or solar adoption alone. From cost-effectiveness perspective, combining TOU and solar in policy programs can also achieve a lower cost per additional adoption of TOU and solar.

Our finding of the correlation between TOU and solar adoption suggests that TOU is associated with the same magnitude of impact as financial instruments such as rebates or tax credits of $2,070~$10,472 (Section 6 shows the details of the calculation). This is significant because currently the nationwide average amount of financial incentives for a solar panel system is $5,493-$9,156. Thus TOU's correlation with solar adoption is equivalent to about 85% of the current size of financial incentives for solar panels.

2. TOU PRICING PLANS OF SALT RIVER PROJECT

The empirical data used in this study is provided by Salt River Project (SRP), one of the largest electric utilities in Arizona. The temperature in Phoenix, Arizona is high in the summer and thus there is a large electricity demand for cooling during peak hours, which contributes to the development of dynamic pricing plans (Kirkeide, 2012). Moreover, Arizona is a good case for studies on solar panel installation due to its large installed capacity and large per capita cumulative solar electric generating capacity (one of top three states in the United States) (Qiu et al., 2017b; Qiu et al., 2019).

We use data of the Residential Equipment and Technology (RET) survey conducted by SRP in 2014. A random selection of SRP residential customers was surveyed using two methods: an online survey and a mail survey. The number of surveys distributed online is 61,925 with 9,389 completed, and that for mail survey is 20,625 with 6,646 completed. SRP also provides a separate dataset which includes the timing of solar panel adoption for each solar customer and a subset of energy efficient AC installations, as well as for each month what type of electricity rate each customer was on. In December 2014, there was a major change in the net metering policy of SRP. However, that policy change would not impact our results because the RET survey was conducted in early 2014.

In 2014, there were six types of electricity rates enrolled by SRP residential consumers, numbered from E-21 to E-26. The price plans listed in Table 1 show the details of the per kWh charges for different pricing plans. The monthly service charge is the same for all the plans and there

Table 1: Salt River Project TOU and standard residential tariffs

Pricing plan	Name	Categories	Summer rates	Summer peak rates	Winter rates	Notes
E-21	Price plan for residential super peak time-of-use service	On peak	$0.3013	$0.3568	$0.1205	On-peak hours year-round consist of those hours from 3 p.m. to 6 p.m.; All other hours are off-peak.
		Off peak	$0.0820	$0.0844	$0.0748	
E-22	Experimental plan for residential super peak time-of-use service	On peak	$0.3013	$0.3568	$0.1205	On-peak hours year-round consist of those hours from 4 p.m. to 7 p.m.; All other hours are off-peak.
		Off peak	$0.0820	$0.0844	$0.0748	
E-23	Standard price plan for residential service (non-TOU)	≤ 700 kWh	$0.1082	$0.1148	$0.0793	No increasing block during winter months.
		701-2,000 kWh	$0.1101	$0.1160	$0.0793	
		All Additional kWh	$0.1206	$0.1311	$0.0793	
E-25	Experimental plan for residential super peak time-of-use service	On-peak	$0.3013	$0.3568	$0.1205	On-peak hours year-round consist of those hours from 2 p.m. to 5 p.m.; All other hours are off-peak.
		Off-peak	$0.0820	$0.0844	$0.0748	
E-26	Standard price plan for residential time-of-use service	On-peak	$0.1937	$0.2206	$0.1010	Summer On-peak hours consist of those hours from 1 p.m. to 8 p.m.; winter on-peak hours consist of hours from 5 a.m. to 9 a.m. and from 5 p.m. to 9 p.m.
		Off-peak	$0.0718	$0.0721	$0.0701	

is no demand charge. Among them, E-23 and E-24 are non-dynamic rates (flat rates) while the rest are TOU rates. We drop households in the M-power program (E-24 plan), because E-24 is a prepaid electricity plan and provides consumers with extra information on usage through an in-home display and thus these consumers respond differently than consumers on other plans (Qiu et al., 2017c). The flat rate is an increasing block rate and its marginal electricity price does not differ by time of day. The four TOU rates (E-21, E-22, E-25, and E-26) differ in their on-peak times and peak hour prices for a given day.

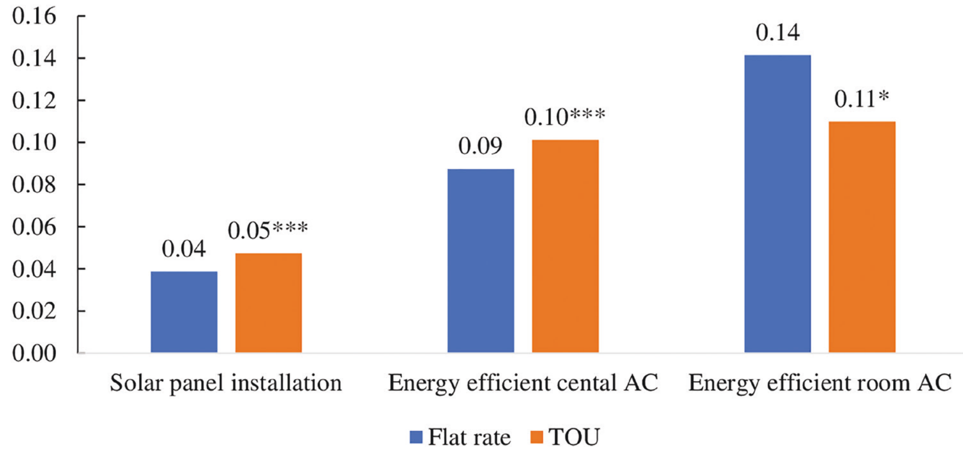
The survey asks questions about the adoption of different appliances including central air conditioner and room air conditioner, and adoption of solar panels. The participants are asked to report whether they replaced any appliance during the last 3 years and whether the appliance was replaced by an energy efficient alternative, i.e., Energy Star certified appliance. Energy Star is considered more energy efficient compared to uncertified ones because the certified products exceed the federal energy efficiency standard. The survey also includes questions about the consumers' electricity pricing plans, building characteristics (square footage, stories, vintage, residence type, etc.) and socio-demographics (household income, household size, race, age of household head, etc.). The renter/owner information was obtained separately from Nielsen. Different kinds of dwelling are covered in this study, including single family home, mobile home and apartment/condo/townhouse.

3. METHODOLOGY

3.1 Summary statistics

We focus on energy efficient air conditioner units rather than other appliances because air conditioning accounts for 6% of all the electricity produced in the U.S. and the electricity use from AC also increases the fastest among appliances (Boomhower and Davis, 2019). An understanding of the relationship between TOU and energy efficient AC adoption can provide insights into the

Figure 2: Adoption of energy efficient air conditioners and solar panels



Notes: The vertical axis is the saturation level (with the range from 0 to 1) of the energy efficient air conditioners or solar panels; the denominators for the saturation level calculation are the number of customers who reported whether they have the technologies or not; *** means statistically different by t-test at 1% level; * is at 10% level. Color figure is available online.

influences of TOU on other appliances. Figure 2 shows that the adoption of solar panels, energy efficient central air conditioners, and room air conditioners are higher for TOU consumers than non-TOU consumers. Figure 3 is a map showing the uptake of solar, energy efficient AC, and TOU at the zip code level. In addition to central AC, we also analyze the adoption of energy efficient room air conditioners because this should be useful for policy-makings in the developing countries where room air conditioners are more widely adopted compared to central air conditioners.

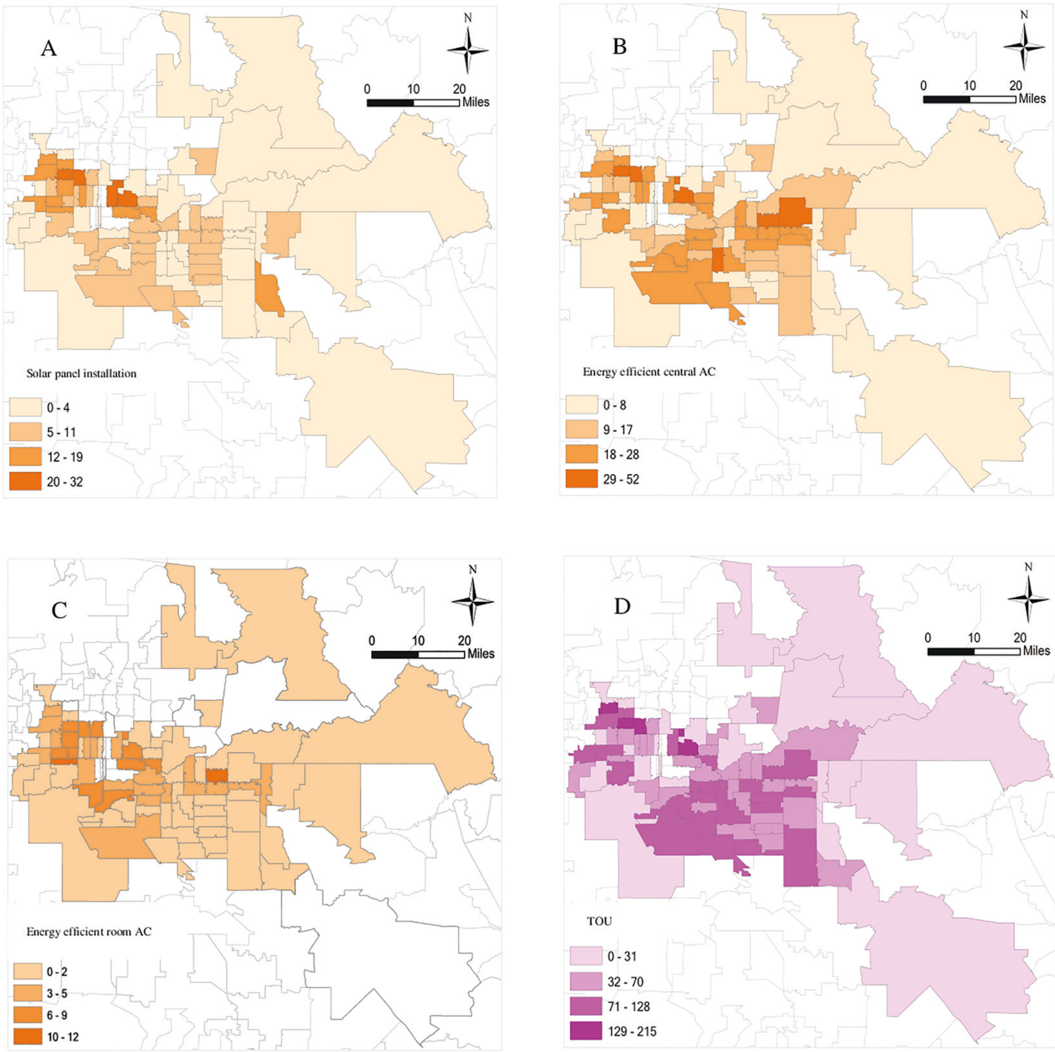
Certain characteristics between TOU consumers and flat rate consumers differ (Table 2). TOU consumers have higher monthly electricity usage, higher household income, and larger square footage. Their houses are more likely to be a primary residence rather than a seasonal residence, and the houses are more likely to have a swimming pool and programmable thermostats. Additionally, the non-TOU households have a longer vintage of the house and an older household head.

It is possible that some consumers first adopt solar panels or energy efficient AC units and then switch to TOU plans—a reverse causality problem. However, this is not a major concern in this study. For all 558 solar customers in the RET survey, only 7 solar customers switched to TOU after they adopted solar panels. We dropped these 7 solar customers in order to help avoid reverse causality. On average, based on SRP's customer level data, the solar customers adopted solar panels five years later than the time when they started on TOU rates. Similarly, the timing of energy efficient appliances adoption is later than TOU enrollment. The adoption of energy efficient appliances in our dataset happens after 2011 while average timing for TOU enrollment is between 2007 and 2008. Because of the long lag (several years) between TOU enrollment and solar adoption, it is unlikely that TOU consumers are forward-looking. In other words, it is not likely that they take into consideration the possibility of adopting solar when making the decision of enrolling in TOU.

3.2 Matching

In empirical studies, randomized control trials and natural experiments are ideal strategies to evaluate a causality relationship (Alberini and Towe, 2015). Given only observational data are available in this study, we use a matching approach to approximate a randomized experiment

Figure 3: Uptake of solar panels (A), energy efficient central AC (B), energy efficient room AC (C) and TOU rates (D)



Notes: Color indicates number of adoptions based on the survey responses. Color figure is available online.

(Stuart, 2010). The control group is matched with the treated group, and these two groups are very similar based on observables except the variable of interest (i.e. the treatment variable). Matching reduces the imbalance between the treated and untreated groups conditional on control variables. There are different matching methods, among which propensity score matching is the most widely adopted while coarsened exact matching is applied more frequently in recent studies (Stuart, 2010). Propensity score matching and coarsened exact matching represent two known classes of matching (Rubin, 1976; Iacus et al., 2011), which are "equal percent bias reducing" (i.e., makes the means of covariates closer by the same amount) and "Monotonic Imbalance Bounding" (i.e., guarantees a reduction of imbalance). Coarsened exact matching coarsens the variables into strata and prunes both the treated and control variables (Iacus, et al., 2012) while propensity score matching is based on the probability of being treated (Dehejia and Wahba, 2002). Balance checking is necessary for propensity score matching. The matching solution for propensity score matching is ex-ante and

Table 2: Summary statistics of building characteristics and demographics for TOU and flat rate consumers

Variable	Obs	Mean	Std. Dev.	Min	Max
Flat rate					
Energy efficient central AC adoption	7,988[a]	0.087	0.282	0	1
Solar panel installation	8,450	0.039	0.193	0	1
Energy efficient room AC adoption	1,025[b]	0.141	0.349	0	1
Ownership[c] (renter=0)	8,582	0.730	0.444	0	1
Monthly electricity usage (1000 kWh)	8,582	1.349	0.760	0[d]	2.6
Household income ($1000)	8,582	46.012	41.175	0	150
Square footage (1000 ft^2)	8,130	1.516	0.794	.75	3
Persons in household	8,161	2.077	1.058	1.5	5
White (non-white=0)	8,035	0.755	0.430	0	1
Stories	7,908	1.167	0.413	1	3
Vintage (in years)	8,582	30.013	19.584	0	65
Age of household head	7,875	60.270	14.690	21	75
Primary (seasonal residence=0)	8,260	0.899	0.301	0	1
Swimming pool	8,495	0.158	0.365	0	1
Programmable thermostats	8,582	0.539	0.499	0	1
Dwelling (apartment=0)					
Mobile house[e]	8,095	0.047	0.212	0	1
Single family house	8,095	0.751	0.432	0	1
TOU					
Energy efficient central AC adoption	4,780	0.101	0.302	0	1
Solar panel installation	4,881	0.047	0.212	0	1
Energy efficient room AC adoption	583[b]	0.110	0.313	0	1
Ownership	4,902	0.732	0.443	0	1
Monthly electricity usage (1000 kWh)	4,902	1.666	0.861	0	2.6
Household income ($1000)	4,902	61.974	45.114	0	150
Square footage (1000 ft^2)	4,794	1.875	0.787	.75	3
Persons in household	4,777	2.416	1.231	1.5	5
White	4,640	0.753	0.431	0	1
Stories	4,689	1.273	0.488	1	3
Vintage	4,902	27.022	17.744	0	65
Age of household head	4,648	54.062	15.758	21	75
Primary (seasonal residence=0)	4,829	0.977	0.151	0	1
Swimming pool	4,886	0.405	0.491	0	1
Programmable thermostats	4,902	0.666	0.472	0	1
Dwelling (apartment=0)					
Mobile house	4,733	0.011	0.103	0	1
Single family house	4,733	0.831	0.375	0	1

[a] The number of energy efficient central AC adoption is smaller than the number of solar panel installation because fewer people reported on this variable;
[b] This is the number of people that reported whether they adopted energy efficient room AC or not. There are 11,882 households without room air conditioners and thus adoption of energy efficient room AC does not apply to them;
[c] Data from Nielsen. Ownership is coded as 1 if the "homeowner or renter status" is described as "definite owner" or "probable owner". It is coded as 0 if the status is "definite renter" or "probable renter";
[d] The averaged usage is calculated by diving the total usage from June through September by the number of billing months. A consumption of zero indicates the house is probably vacant;
[e] Mobile house refers to a permanent or semi-permanent residence that can be moved.

balance is ex-post. In contrast, for coarsened exact matching, the amount of imbalance is controlled ex-ante (Blackwell et al., 2009). Both matching methodologies will be applied. The analysis is at the household level. After matching, standardized mean difference (SMD) and variance ratio (VR) are applied to assess the quality of balancing, which are defined as $SMD = \frac{\bar{X}_{Treat} - \bar{X}_{Control}}{\sqrt{(S^2_{Treat} + S^2_{Control})/2}}$ and $VR = \frac{S^2_{Treat}}{S^2_{Control}}$, where $\boldsymbol{X}$ is the vector of control covariates, $\bar{X}$ is the mean and s^2 is the variance. Variance ratio should be close to one, and a nearly balance variance ratio should be $4/5 < VR < 5/4$ (Steiner et al., 2010). SMD should be smaller than 0.25 to indicate good balance (Rubin, 2001). All control variables including the demographic and housing characteristics are used as matching variables. In particular, we match on the variables listed in Table 6.

3.3 Basic model specification

A binomial probit model is applied to examine the relationship between TOU and energy efficiency or solar panel adoption.

$$y_i = \begin{cases} 1 \; if \; y_i^* > 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

$$y_i^* = \beta_0 + \beta_1 \left(TOU_i \right) + \beta_2 \boldsymbol{X_i} + \varepsilon_i \tag{2}$$

where i indicates individual household i; y_i is a binary dependent variable indicating the adoption of an energy efficient air conditioner or solar panels. y_i^* is the latent variable; TOU is equal to 1 if the household is on a TOU pricing plan and is 0 if the household is on a flat rate plan. $\boldsymbol{X}$ is a vector of control variables, including demographics (age, households, income, etc.) and housing characteristics (square footage, ownership, stories, etc.). Among $\boldsymbol{X}$, we use the adoption of programmable thermostat as a proxy for environmental awareness. One might argue that the adoption of programmable thermostat itself is endogenous. However, we are not focused on interpreting the coefficient for programmable thermostat adoption. This variable only serves the purpose as a control variable to help eliminate the omitted variable bias from the lack of environmental awareness data. In other words, by including the adoption of programmable thermostat, the part of the error terms that is due to environmental awareness is now controlled for and thus the rest of the error terms are no longer correlated with the TOU variable (Stock & Watson, 2007). Although there are financial incentives for the adoption of energy efficient appliances or solar panels, there is no variation for these incentives in our dataset because all consumers are served by the same utility company and the same incentives are available to all of the utility's consumers. Although characteristics such as the shade condition and roof direction might impact solar panel adoption, these impacts are assumed to be random and uncorrelated with the adoption of TOU pricing. Thus, shade condition and roof direction do not interfere with the estimates of the impacts of TOU.

4. ECONOMETRIC ANALYSIS

4.1 Coarsened exact matching

Each column in Table 3 is a single probit regression on the matched control and treatment customers after coarsened exact matching. Models in column (1), (4) and (7) simply regress the adoption of energy efficiency or solar panels on TOU, while columns (2), (5) and (8) include household characteristics and demographics as control variables in the models. The models in the columns (3), (6) and (9) further add the district dummy variables (zip code). Means of variables before and after matching among TOU and non-TOU consumers are presented in Table 4, which indicates that the control group and treatment group are well balanced. Coarsened exact matching achieves common support because all observations within a stratum containing both a treated and control unit are by definition inside of the common support.

The main result from Table 3 is that there is a positive correlation between TOU and solar panel installation. There is no evidence that TOU consumers are more likely to adopt energy

Table 3: Adoption of energy efficiency or solar panels for treatment groups and control groups using coarsened exact matching and weighted probit model[a]

	Solar panel installation				Energy efficient central AC				Energy efficient room AC			
	(1) Probit model	(2) Probit model	(3) Probit model	Marginal effect	(4) Probit model	(5) Probit model	(6) Probit model	Marginal effect	(7) Probit model	(8) Probit model	(9) Probit model	Marginal effect
TOU	0.143	0.197**	0.176*	0.014*	0.091	0.099	0.087	0.015	0.157	0.112	0.062	0.010
	(0.093)	(0.100)	(0.098)	(0.007)	(0.063)	(0.065)	(0.064)	(0.011)	(0.187)	(0.208)	(0.265)	(0.041)
Ownership (renter=0)		–0.589**	–0.519*	–0.040*		0.515**	0.586**	0.100**		4.292***	5.098***	0.793***
		(0.275)	(0.297)	(0.023)		(0.240)	(0.244)	(0.042)		(0.543)	(0.990)	(0.163)
Monthly electricity usage (1000 kWh)		–0.199**	–0.196*	–0.015**		0.067	0.072	0.012		–0.081	–0.274	–0.043
		(0.101)	(0.100)	(0.008)		(0.061)	(0.063)	(0.011)		(0.200)	(0.240)	(0.037)
Household income ($1000)		–0.001	–0.0002	–0.00001		0.001	0.001	0.0002		0.003	0.007*	0.001*
		(0.002)	(0.002)	(0.0001)		(0.001)	(0.001)	(0.0002)		(0.003)	(0.005)	(0.001)
Square footage (1000 ft^2)		0.115	0.126	0.010		–0.047	–0.045	–0.008		–0.234	–0.202	–0.031
		(0.084)	(0.082)	(0.006)		(0.050)	(0.052)	(0.009)		(0.161)	(0.197)	(0.030)
Persons in household		0.062	0.062	0.005		–0.011	–0.029	–0.005		0.172	0.205	0.032
		(0.067)	(0.067)	(0.005)		(0.038)	(0.036)	(0.006)		(0.131)	(0.150)	(0.023)
White (non-white=0)		–0.041	–0.032	–0.002		0.107	0.095	0.016		0.794**	1.006**	0.157**
		(0.150)	(0.154)	(0.012)		(0.089)	(0.093)	(0.016)		(0.313)	(0.472)	(0.070)
Stories		0.014	–0.033	–0.003		–0.298***	–0.299***	–0.051***		0.471	0.754**	0.117**
		(0.176)	(0.179)	(0.014)		(0.106)	(0.110)	(0.019)		(0.353)	(0.354)	(0.054)
Vintage (in years)		0.007*	0.011**	0.001**		–0.004*	–0.00002	–3.8e–06		–0.002	–0.021	–0.003
		(0.004)	(0.005)	(0.0004)		(0.002)	(0.003)	(0.001)		(0.007)	(0.014)	(0.002)

(continued)

Table 3: Adoption of energy efficiency or solar panels for treatment groups and control groups using coarsened exact matching and weighted probit model[a] *(continued)*

	Solar panel installation				Energy efficient central AC				Energy efficient room AC			
	(1) Probit model	(2) Probit model	(3) Probit model	Marginal effect	(4) Probit model	(5) Probit model	(6) Probit model	Marginal effect	(7) Probit model	(8) Probit model	(9) Probit model	Marginal effect
Age of household head		0.017***	0.023***	0.002***		–0.001	0.001	0.0002		0.023*	0.030**	0.005**
		(0.005)	(0.006)	(0.0004)		(0.003)	(0.003)	(0.001)		(0.013)	(0.015)	(0.002)
Primary (seasonal residence=0)		–0.033	0.074	0.006		0.102	0.088	0.015		—[b]	—	—
		(0.311)	(0.308)	(0.024)		(0.296)	(0.324)	(0.055)		—	—	—
Swimming pool		0.178	0.238**	0.018**		–0.087	–0.116	–0.020		–0.193	–0.093	–0.014
		(0.120)	(0.119)	(0.009)		(0.081)	(0.079)	(0.013)		(0.281)	(0.304)	(0.047)
Dwelling type(apartment=0)												
Mobile house		—	—	—		–0.110	–0.257	–0.038		—	—	—
		—	—	—		(0.380)	(0.381)	(0.049)		—	—	—
Single family house		0.579**	0.499**	0.028***		–0.072	0.006	0.001		–0.100	0.249	0.037
		(0.229)	(0.250)	(0.010)		(0.149)	(0.151)	(0.026)		(0.671)	(0.806)	(0.112)
Programmable thermostats		0.067	0.062	0.005		0.356***	0.325***	0.055***		0.127	0.176	0.027
		(0.105)	(0.106)	(0.008)		(0.075)	(0.075)	(0.013)		(0.206)	(0.261)	(0.041)
Constant	–1.884***	–3.158***	–4.041***		–1.281***	–1.658***	–2.253***		–1.445***	–8.121***	–10.210***	
	(0.075)	(0.641)	(0.818)		(0.050)	(0.458)	(0.565)		(0.140)	(1.008)	(1.714)	
N	3,947	3,763	3,200	3,200	4,245	4,078	4,039	4,039	431	413	256	256
Area (zip codes)	No	No	Yes[c]		No	No	Yes[c]		No	No	Yes[d]	
Wald chi2	2.33***	84.42***	189.27***		2.07	98.56***	227.93***		0.71	606.73*	383.67***	
Pseudo R^2	0.003	0.072	0.138		0.001	0.045	0.096		0.003	0.148	0.320	

[a] The matching is acceptable when the multivariate L1 distances reduce, which indicates the imbalance is reduced after matching;
[b] Variable is dropped because it predicts failure perfectly;
[c] 84 zip codes;
[d] 26 zip codes.
Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Weighted means[a] and standard errors of matching variables for TOU and non-TOU consumers using coarsened exact matching (analysis of solar panel installation)

	Before matching				After matching			
	Non-TOU		TOU		Non-TOU		TOU	
Variable	Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean
Ownership	7,763	0.725 (0.446)	4,362	0.720 (0.449)	2,296	0.768 (0.422)	1,675	0.768 (0.422)
Usage	7,763	1.338 (0.761)	4,362	1.654 (0.868)	2,296	1.587 (0.770)	1,675	1.621 (0.784)
Household income	7,763	45.341 (40.871)	4,362	61.310 (44.969)	2,296	57.973 (38.872)	1,675	58.831 (39.815)
Square footage	7,328	1.510 (0.795)	4,264	1.864 (0.793)	2,277	1.732 (0.755)	1,662	1.732 (0.755)
Persons in household	7,366	2.065 (1.052)	4,252	2.413 (1.230)	2,285	2.064 (1.006)	1,668	2.064 (1.006)
White	7,256	0.751 (0.433)	4,124	0.746 (0.435)	2,257	0.831 (0.375)	1,644	0.831 (0.375)
Stories	7,118	1.171 (0.418)	4,155	1.275 (0.493)	2,275	1.135 (0.362)	1,654	1.135 (0.362)
Vintage	7,763	29.911 (19.765)	4,362	26.867 (17.936)	2,296	27.648 (18.717)	1,675	27.570 (18.067)
Household head age	7,088	60.383 (14.744)	4,136	53.849 (15.964)	2,261	56.936 (15.238)	1,648	56.527 (15.443)
Primary residence	7,454	0.898 (0.302)	4,291	0.976 (0.154)	2,290	0.990 (0.100)	1,671	0.990 (0.100)
Swimming pool	7,677	0.156 (0.363)	4,346	0.401 (0.490)	2,296	0.343 (0.475)	1,675	0.343 (0.475)
Dwelling type								
Mobile home	7,299	0.045 (0.208)	4,196	0.011 (0.103)	2,280	0.008 (0.088)	1,658	0.008 (0.088)
Single family house	7,299	0.745 (0.436)	4,196	0.822 (0.383)	2,280	0.821 (0.383)	1,658	0.821 (0.383)
Programmable thermostats	7,763	0.524 (0.499)	4,362	0.651 (0.477)	2,296	0.641 (0.480)	1,675	0.641 (0.480)

[a] Weighted means after matching indicates the observations are weighted. Unmatched units get weights of zero. A weight of 1 is given to matched units in the treated group and weights of $\frac{m_C}{m_T}\frac{m_T^S}{m_C^s}$ are given to matched units in the control group, where m_T^S and m_C^s are treated and untreated units in stratum s.

efficient central AC or room AC. The coefficients on TOU for energy efficient AC units are small and statistically insignificant. TOU consumers are more likely to install solar panels (based on marginal effects 1.4 percentage point, $p<0.10$) (column (3)). The marginal effect is calculated using $\partial \text{prob}(y_i=1)/\partial TOU_i$ for a reference individual. The mean of the solar adoption variable in the sample is 0.043. Thus 1.4 percentage point increase equals 32.5% (1.4/4.3=32.5%) increase on average in solar panel adoption.

Our finding is supported by several existing studies. Borenstein (2008) found that solar electricity generation occurs disproportionately at times when the electricity price is higher. TOU rate with the peak hours coincident more with solar generation thus benefits solar consumers more (McLaren et al., 2015). As a result, TOU provides indirect incentives for adopting solar panels. The economic benefits of solar installation are even larger when TOU is coupled with net metering (Darghouth et al., 2011) or battery storage, which could save or store electricity for later use. From the consumers' perspective, if they observe or expect this situation, a TOU rate structure could incentivize solar adoption. In the case of the utility price plans in this paper, although the peak hours of TOU and solar irradiance hours do not exactly overlap, the partial overlapping still generates greater economic benefits to PV owners compared to a flat rate. Three other possibilities to explain the impact of TOU on PV adoption might exist, similar to those discussed in Comin and Rode (2015) about the impact of PV adoption on voting for the Green Party. First, TOU helps the consumers gain more net benefits, which may enable the consumers to use the money from TOU to further invest in green technologies such as solar PV. However, according to existing studies, the net savings from TOU are comparably small. Residential consumers save about 2.2% on their electricity bills from TOU (Torriti, 2012) and commercial consumers save about 5–6% (Qiu et al., 2018). Since the money saved is not large enough to compensate for the cost of installing PV, we think it only partially explains the link at best. The second potential mechanism is through Bayesian learning. Consumers could acquire additional information about solar PV values with the TOU adoption, which helps to reduce the uncertainty regarding the value of solar PV. The third mechanism is cognitive dissonant. The consumers change their appreciation for green technologies to get greater utility from past TOU adoption decisions.

For the other variables, a house with longer vintage, more senior household head, or a swimming pool is associated with a higher likelihood of solar panel adoption, as is a single-family house compared to apartment or mobile house. In contrast, a house with higher monthly electricity usage during summer or owner-occupied is associated with lower likelihood of installing solar panels after controlling for other related variables. A house occupied by the owner or with programmable thermostats is more likely to adopt energy efficient central AC while a house with more stories is less likely to adopt energy efficient central AC. In terms of the adoption of energy efficient room AC, an owner-occupied house or if the race of the owner happens to be white, a house with more stories, more senior household head or higher-income households is associated with higher probability of adopting energy efficient room AC.

4.2 Propensity score matching

Similar to the coarsened exact matching, the demographics and building characteristics are used as the matching variables for propensity score matching. Different algorithms of propensity score matching are attempted, including radius matching with different calipers, kernel matching, k-nearest neighbors matching. The results after propensity score matching of different algorithms are very similar. The results with the smallest median bias, as listed in Table 5, are yielded by using the radius matching. Radius matching finds a control for a treated individual only within the caliper (e.g., 0.01), which puts a tolerance level on the largest acceptable propensity score distance. Logit model is used to generate propensity scores. The results show TOU consumers are 0.9 percentage point more likely to adopt solar panels, and the coefficient is statistically significant at the 10-percent level. The correlation between TOU enrollment and energy efficiency adoption is small in magnitude and statistically insignificant. Means of the variables before and after matching among TOU and non-TOU consumers are listed in Table 6. All the variables in the control group are comparable to those in the treatment group after a balancing check using SMD and VR. Figure 4 confirms the common support assumption.

We further add on-peak prices into the model in order to test whether a higher peak price is correlated with higher energy efficient air conditioner and solar panel adoption. Table A1 in the Appendix shows that the coefficients on the interaction term between TOU and peak rate are not statistically significant both before and after matching. Theoretically, when TOU peak rate is higher, there should be more adoption of solar panels, and the coefficient should have a positive sign. The possible reason for the insignificance is that there are only two different peak rates for different TOU rates, which are \$0.3568 and \$0.2206. Hence, TOU peak rates lack sufficient variation for its positive relationship with TOU*(peak price) to be reflected empirically.

Table 5: Adoption of energy efficiency or solar panels for treatment groups and control groups using propensity score matching and weighted probit model

	Solar panels installation				Energy efficient central AC				Energy efficient room AC			
	(1) Probit model	(2) Probit model	(3) Probit model	Marginal effect	(4) Probit model	(5) Probit model	(6) Probit model	Marginal effect	(7) Probit model	(8) Probit model	(9) Probit model	Marginal effect
TOU	0.131**	0.120**	0.107*	0.009*	–0.001	–0.013	–0.027	–0.005	–0.074	–0.082	–0.137	–0.024
	(0.058)	(0.059)	(0.060)	(0.005)	(0.041)	(0.041)	(0.042)	(0.007)	(0.118)	(0.124)	(0.140)	(0.024)
Ownership		0.096	0.144	0.012		0.101	0.159	0.028		0.263	0.519	0.089
(renter=0)		(0.203)	(0.198)	(0.016)		(0.122)	(0.124)	(0.022)		(0.337)	(0.409)	(0.070)
Monthly electricity		–0.262***	–0.269***	–0.022***		–0.004	0.003	0.0005		0.037	0.029	0.005
usage (1000 kWh)		(0.041)	(0.042)	(0.004)		(0.031)	(0.031)	(0.005)		(0.100)	(0.109)	(0.019)
Household income		0.0002	0.0001	1.0e–05		0.001*	0.001*	0.0002*		–0.002	–0.001	–0.0002
($1000)		(0.001)	(0.001)	(0.00008)		(0.001)	(0.001)	(0.0001)		(0.002)	(0.002)	(0.0004)
Square footage		0.153***	0.164***	0.014***		–0.059*	–0.045	–0.008		–0.034	0.066	0.011
(1000 ft^2)		(0.050)	(0.053)	(0.004)		(0.031)	(0.033)	(0.006)		(0.089)	(0.104)	(0.018)
Persons in household		0.049*	0.050*	0.004*		–0.002	0.008	0.001		0.146***	0.122**	0.021**
		(0.027)	(0.028)	(0.002)		(0.020)	(0.020)	(0.004)		(0.054)	(0.060)	(0.010)
White (non-white=0)		–0.071	–0.041	–0.003		0.124**	0.107**	0.019**		0.500***	0.431**	0.074**
		(0.075)	(0.081)	(0.007)		(0.052)	(0.054)	(0.010)		(0.153)	(0.178)	(0.031)
Stories		–0.062	–0.097	–0.008		–0.112**	–0.107**	–0.019**		0.200	0.273	0.047
		(0.076)	(0.078)	(0.006)		(0.050)	(0.050)	(0.009)		(0.156)	(0.171)	(0.030)
Vintage (in years)		–0.000	0.001	0.00005		–0.007***	–0.005***	–0.001***		0.004	0.005	0.001
		(0.002)	(0.003)	(0.0002)		(0.002)	(0.002)	(0.0004)		(0.005)	(0.006)	(0.001)

(continued)

Table 5: Adoption of energy efficiency or solar panels for treatment groups and control groups using propensity score matching and weighted probit model *(continued)*

	Solar panels installation				Energy efficient central AC				Energy efficient room AC			
	(1) Probit model	(2) Probit model	(3) Probit model	Marginal effect	(4) Probit model	(5) Probit model	(6) Probit model	Marginal effect	(7) Probit model	(8) Probit model	(9) Probit model	Marginal effect
Age of household head		0.012***	0.014***	0.001***		0.0005	0.001	0.0002		0.011**	0.011**	0.002**
		(0.003)	(0.003)	(0.0002)		(0.002)	(0.002)	(0.0003)		(0.006)	(0.006)	(0.001)
Primary (seasonal residence=0)		0.609***	0.709***	0.059***		0.152	0.126	0.022		0.158	–0.082	–0.014
		(0.184)	(0.178)	(0.015)		(0.118)	(0.124)	(0.022)		(0.356)	(0.357)	(0.061)
Swimming pool		0.193***	0.219***	0.018***		–0.045	–0.059	–0.010		0.072	0.080	0.014
		(0.068)	(0.069)	(0.006)		(0.049)	(0.051)	(0.009)		(0.146)	(0.156)	(0.027)
Dwelling type(apartment=0)												
Mobile house		0.009	–0.163	–0.009		0.266	0.218	0.036		0.726**	0.600	0.111
		(0.376)	(0.372)	(0.018)		(0.171)	(0.181)	(0.033)		(0.337)	(0.421)	(0.092)
Single family house		0.281**	0.198	0.015*		0.149*	0.184**	0.030**		0.231	0.280	0.044
		(0.116)	(0.122)	(0.008)		(0.078)	(0.080)	(0.012)		(0.222)	(0.268)	(0.039)
Programmable thermostats		0.025	0.037	0.003		0.389***	0.386***	0.068***		0.134	0.144	0.025
		(0.064)	(0.064)	(0.005)		(0.047)	(0.047)	(0.008)		(0.123)	(0.137)	(0.024)
Constant	–1.811***	–3.299***	–3.469***		–1.219***	–1.491***	–1.760***		–1.271***	–3.587***	–0.772	
	(0.045)	(0.353)	(0.474)		(0.030)	(0.219)	(0.290)		(0.078)	(0.726)	(1.012)	
N	9,187	9,187	8,682	8,682	9,474	9,474	9,461	9,461	1,084	1,084	847	847
Area (zip codes)	No	No	Yes [a]	No	No	No	Yes [a]		No	No	Yes [b]	
Wald chi2	5.07**	135.42***	259.65***		0.00	191.23***	359.69***		0.39	58.51***	149.02***	
Pseudo R^2	0.002	0.067	0.106		0.000	0.042	0.076		0.001	0.095	0.180	

[a] 84 zip codes;
[b] 46 zip codes.
Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Mean of variables before and after matching in TOU and non-TOU consumers using propensity score matching (analysis of solar panel installation)

	Before matching				After matching			
	Non-TOU		TOU		Non-TOU		TOU	
Variable	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Ownership (renter=0)	7,763	0.725 (0.446)	4,362	0.720 (0.449)	6,158	0.709 (0.454)	3,728	0.712 (0.453)
Monthly electricity usage (1000 kWh)	7,763	1.338 (0.761)	4,362	1.654 (0.868)	6,158	1.606 (0.809)	3,728	1.607 (0.879)
Household income ($1000)	7,763	45.341 (40.871)	4,362	61.310 (44.969)	6,158	64.582 (43.370)	3,728	64.646 (42.583)
Square footage (1000 ft^2)	7,328	1.510 (0.795)	4,264	1.864 (0.793)	6,158	1.816 (0.777)	3,728	1.827 (0.780)
Persons in household	7,366	2.065 (1.052)	4,252	2.413 (1.230)	6,158	2.371 (1.202)	3,728	2.384 (1.218)
White (non-white=0)	7,256	0.751 (0.433)	4,124	0.746 (0.435)	6,158	0.757 (0.429)	3,728	0.762 (0.426)
Stories	7,118	1.171 (0.418)	4,155	1.275 (0.493)	6,158	1.265 (0.499)	3,728	1.256 (0.478)
Vintage (in years)	7,763	29.911 (19.765)	4,362	26.867 (17.936)	6,158	27.034 (18.867)	3,728	27.116 (17.821)
Age of household head	7,088	60.383 (14.744)	4,136	53.849 (15.964)	6,158	53.243 (15.756)	3,728	53.455 (15.715)
Primary (seasonal residence=0)	7,454	0.898 (0.302)	4,291	0.976 (0.154)	6,158	0.979 (0.142)	3,728	0.978 (0.148)
Swimming pool	7,677	0.156 (0.363)	4,346	0.401 (0.490)	6,158	0.365 (0.481)	3,728	0.370 (0.483)
Dwelling type								
Mobile home	7,299	0.045 (0.208)	4,196	0.011 (0.103)	6,158	0.009 (0.096)	3,728	0.010 (0.099)
Single family house	7,299	0.745 (0.436)	4,196	0.822 (0.383)	6,158	0.805 (0.396)	3,728	0.814 (0.390)
Programmable thermostats	7,763	0.524 (0.499)	4,362	0.651 (0.477)	6,158	0.648 (0.478)	3,728	0.651 (0.477)

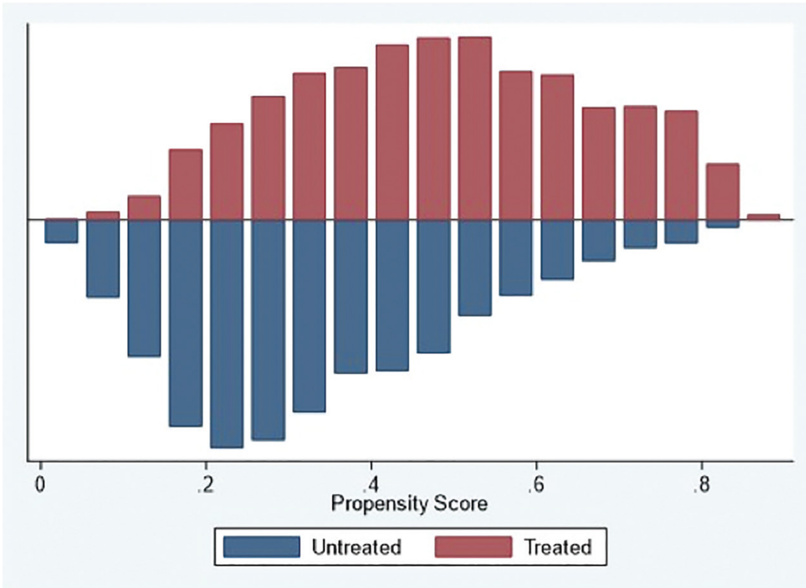
Notes: Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

4.3 Heterogeneity of TOU's correlation with solar panel adoption

We conduct an additional analysis with the renters excluded from our regression models (Table A2 in the Appendix). We find that the results are consistent with those using full sample with both renters and owners, and the magnitudes only differ slightly. The impact of TOU on PV adoption is higher for owners than for renters, which is consistent with the intuition that the owners are more likely to adopt low-carbon technologies. Our main models have controlled for the ownership by including a dummy variable indicating the ownership status.

We conduct separate analyses for mail versus web survey respondents (Table A3 in the Appendix). Theoretically, we would expect that people's adoption of other technologies such as the internet could influence their adoption of green technologies such as solar PV (Comin and Rode, 2015). The results obtained for participants of mail surveys are different from those of web surveys. We found that the results based on mail surveys only are similar to the results of using all surveys. Also, our results are more statistically significant for mail survey respondents. In addition to the difference in the sample size, another potential explanation might be that the mail respondents are more permanent (i.e., more likely to own the house) and thus are more likely to invest in expensive energy technologies such as solar panels.

Figure 4: Check for common support for propensity score matching



Notes: Color figure is available online.

Using the sample from propensity score matching, we also examine if the probability of solar adoption conditional on TOU pricing varies across other consumer/building characteristics (see Appendix B). The characteristics examined are monthly electricity usage, household income, square footage of the property, persons in the household, property vintage (in years), and age of household head.

5. ROBUSTNESS CHECKS

We conduct the following robustness checks to analyze further the differences in the adoption of energy efficient central air conditioners and solar panels between TOU and non-TOU consumers.

5.1 Multinomial logit model

Multinomial logit model is applied to the matched control and treatment groups in order to analyze various combinations of technology choices. The four alternatives of the dependent variable are households with (1) both energy efficient AC and solar panel adopted; (2) only energy efficient AC adopted; (3) only solar panel adopted; (4) none of the two adopted. The number of observed outcomes for the dependent variable is listed in Table 7.

Suppose there are j alternatives, y_j=1 if j is the observed outcome and is 0 otherwise. $y_j = \begin{cases} 1 if\ y = j \\ 0 if\ y \neq j \end{cases}$. The probability that the individual i chooses alternative j is $P_{ij}=P(y_i=j)=$ $\dfrac{\exp(\boldsymbol{w}_i'\gamma_j)}{\sum_{k=1}^{m}\exp(\boldsymbol{w}_i'\gamma_k)}$. P_{ij} is the probability for an individual with characteristics $\boldsymbol{w}_i$ facing m (m=4) choices; $\boldsymbol{w}_i'\gamma_j$ together is equal to equation (2), and the covariates include the specific demographics

Table 7: Distribution of the observed outcomes

	Solar panels	Energy efficient central AC	No. of observations	Percentage of total observations
(1)	No	No	10,816	86.2%
(2)	No	Yes	1,148	9.2%
(3)	Yes	No	514	4.1%
(4)	Yes	Yes	65	0.52%

Notes: We drop the observations with room AC in this robustness checks because the number of households adopting room AC is much smaller than those for central AC. Including room AC into bundles of technologies will complicate the number of choices in multinomial logit models.

Table 8: Adoption of energy efficiency or solar panels for treatment groups and control groups using multinomial logit model

	Solar panel adoption only	Energy efficient central AC only	Adoption of both solar panel and energy efficient central AC
Without matching			
TOU	0.327***	–0.0004	0.095
	(0.126)	(0.075)	(0.289)
N	10,061		
Log pseudolikelihood	–4840.908		
Pseudo R^2	0.051		
Coarsened exact matching			
TOU	0.269	0.112	–1.060*
	(0.246)	(0.137)	(0.586)
N	3,437		
Log pseudolikelihood	–1673.499		
Pseudo R^2	0.065		
Propensity score matching			
TOU	0.274**	–0.026	0.200
	(0.132)	(0.079)	(0.296)
N	9,826		
Log pseudolikelihood	–3857.412		
Pseudo R^2	0.054		

Notes: The base level is the households that neither adopt solar panel nor energy efficient central AC; all the regressions include the demographics and the house characteristics; Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

and housing characteristics for individual i. The results of the multinomial logit model (Table 8) further indicate that TOU consumers are only more likely to install solar panels while TOU does not influence energy efficiency adoption.

5.2 Bivariate probit

A bivariate probit model can also examine the correlation between the adoption of solar panels or energy efficiency and TOU enrollment: $y_i^* = \beta_0 + \beta_1 \boldsymbol{X_i} + \varepsilon_i$, $TOU_i^* = r_0 + r_1 \boldsymbol{X_i} + e_i$, and $\begin{pmatrix} \varepsilon_i \\ e_i \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$. y_i and $\boldsymbol{X_i}$ have the same meaning as indicated in equations (1) and (2). ρ is the correlation coefficient. If ρ is significantly different from zero, the two decisions are interrelated. Table 9 shows that the correlation coefficient ρ is positive and statistically significant for the adoption of solar panels, which indicates that the decision of solar panel installation is correlated with TOU enrollment. However, our estimate of the correlation coefficient ρ is small and statistically insignificant for energy efficient central AC and room AC adoption, suggesting that the adoption of energy efficient AC unit is not correlated with TOU pricing.

Table 9: Adoption of energy efficiency or solar panels and TOU pricing enrollment using a bivariate probit model[a]

	Bivariate probit model for solar panel installation		Bivariate probit model for adoption of energy efficient central AC		Bivariate probit model for adoption of energy efficient room AC	
Dependent variable	Solar panel installation	TOU	Energy efficient central AC	TOU	Energy efficient room AC	TOU
Ownership	0.098	0.050	0.101	0.043	0.250	0.438*
	(0.203)	(0.081)	(0.122)	(0.080)	(0.339)	(0.235)
Usage	-0.262***	-0.026	-0.004	-0.026	0.040	-0.078
	(0.041)	(0.023)	(0.031)	(0.023)	(0.100)	(0.068)
Household income	0.0002	0.0008	0.001*	-0.0001	-0.002	-0.001
	(0.001)	(0.000)	(0.001)	(0.0005)	(0.002)	(0.001)
Square footage	0.152***	-0.010	-0.059*	-0.0001	-0.036	0.095
	(0.050)	(0.024)	(0.031)	(0.024)	(0.088)	(0.069)
Persons in household	0.050*	0.012	-0.002	0.010	0.147***	-0.037
	(0.027)	(0.015)	(0.020)	(0.015)	(0.054)	(0.040)
White	-0.071	0.004	0.124**	0.0001	0.496***	0.097
	(0.075)	(0.038)	(0.052)	(0.037)	(0.152)	(0.100)
Stories	-0.063	-0.037	-0.112**	-0.030	0.197	0.085
	(0.076)	(0.035)	(0.050)	(0.035)	(0.156)	(0.102)
Vintage	-0.001	-0.003***	-0.007***	-0.003**	0.005	-0.014***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.005)	(0.004)
Household head age	0.012***	0.0004	0.0005	0.0004	0.011*	0.006
	(0.003)	(0.001)	(0.002)	(0.001)	(0.006)	(0.004)
Primary residence	0.607***	-0.027	0.152	-0.037	0.152	0.204
	(0.183)	(0.086)	(0.118)	(0.083)	(0.358)	(0.288)
Swimming pool	0.193***	0.019	-0.045	0.002	0.074	-0.044
	(0.067)	(0.038)	(0.049)	(0.037)	(0.146)	(0.116)
Programmable thermostats	0.025	-0.004	0.389***	-0.023	0.138	-0.143
	(0.064)	(0.032)	(0.047)	(0.032)	(0.123)	(0.090)
Dwelling (apartment=0)						
Single family house	0.009	0.006	0.266	-0.019	0.740**	-0.465
	(0.376)	(0.131)	(0.171)	(0.130)	(0.337)	(0.332)
Mobile house	0.281**	0.001	0.149*	0.012	0.233	-0.058
	(0.116)	(0.051)	(0.078)	(0.050)	(0.221)	(0.158)
Constant	-3.227***	0.143	-1.498***	0.159	-3.617***	-0.261
	(0.353)	(0.158)	(0.218)	(0.154)	(0.724)	(0.460)
		0.075**		-0.008		-0.051
		(0.037)		(0.026)		(0.077)
N		9,187		9,474		1,084

[a] The regression uses the matched sample from propensity score matching; the specifications are without areas included because the standard errors are inflated by collinearity if areas are all included.
Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

5.3 Matching using machine learning

Machine learning approach is adopted by using classification and regression trees (CART)-based propensity score model (see details of the methods and results in Appendix C). CART-based model uses decision trees or regression trees to incorporate additionality, interaction and non-linearity (Lee et al., 2010). Boosted CART is used based on *twang* package (Ridgeway et al., 2015). The results show that the positive correlation between solar panel installation and TOU enrollment still holds while the coefficient on TOU is not statistically significant for the analysis of energy efficient central AC.

6. MONETARY VALUATION OF TOU'S ASSOCIATION WITH SOLAR ADOPTION

6.1 Remaining issues and usefulness of our results

We use a matching approach plus controlling for a rich set of covariates to try to identify the impact of TOU on solar panel and energy efficiency adoption. The key assumption for a causal identification using our approach is that the factors influencing the TOU enrollment and technology adoption are observable. Our estimated correlation might not reflect the causal relationship if there are unobservables impacting both TOU enrollment and solar or energy efficiency adoption. Examples of these unobservables include whether local solar contractors' marketing information includes the benefits of TOU, individual consumers' energy financial literacy, and so on.

Estimating the correlation, although not fully causal, between TOU and solar adoption is still meaningful. For example, if indeed one of the unobservables is whether a household has encountered a local solar contractor that promotes the large benefit from solar under TOU, then our results would imply that such marketing campaign bundling TOU and solar could potentially be effective at promoting both TOU and solar adoption. If the unobservable is energy financial literacy (although this unobservable could be partially controlled for using our programmable thermostat variable), then our results would imply that policy makers should identify the group of consumers that are environmentally friendly and energy-savvy and then bundle TOU and solar together when providing educational programs to these consumers.

To better justify that our estimated correlation is causal, in future studies better data are needed such as information on exogenous variation impacting TOU enrollment. In terms of external validity, our study only examines the TOU plan under SRP's service territory. In some other states, TOU peak hours are in different hours than the ones with SRP, which could imply different magnitudes of correlation between TOU and solar adoption.

6.2 Emission impact of TOU-correlated solar panel adoptions

In light of the estimated correlation between solar-panel adoption and TOU pricing, we now assess the emission impacts associated with the additional solar-panels correlated with TOU enrollment. We first come up with an assessment of how many solar panel installations are associated with TOU pricing as of 2014 in SRP's service territory using our estimated impact of TOU. Next, we combine this assessment with the estimated reduction in greenhouse-gas and environmental pollution emissions per installation to obtain the overall emission impact. We obtain estimates of emission reductions from solar panels using average hourly marginal damages of different emissions (CO_2, SO_2, NO_X, and particulate matter) per kWh from (Holland et al., 2016) and simulated hourly electricity generation using PVWATTS model. Details of calculation can be found in Appendix D.

We get the total annual savings from solar panel installation correlated with TOU enrollment. The results are summarized in Appendix Table D1. As the final row of Table D1 indicates, the annual monetary equivalent of emission reduction is approximately \$0.42 million.

6.3 Fiscal-subsidy equivalent of TOU impact

In this section, we conduct a back-of-the-envelope analysis to quantify what dollar amount of financial incentive would achieve the same impact on solar adoption associated with TOU pricing (detailed calculations can be found in Appendix D). TOU is estimated to be associated with the same magnitude of impact on promoting solar adoption as an increase in financial incentives (such as rebates and tax credits) by \$2,070~\$10,472. The average nationwide financial incentives for solar panel adoption are \$5,493-\$9,156. The association between TOU and solar adoption is thus equivalent to about 85% (based on (2,070+10,472)/(5,493+9,156)) of the amount of existing financial incentives. Note our back-of-the-envelope calculation imposes restrictive assumptions including a linear relationship between monetary incentive and adoption rate. When we assume a more realistic, decreasing influence of monetary impact, our calculations should be treated as the upper bound. Nonetheless, these calculations provide us a ballpark number on the monetary equivalence effect regarding the association between TOU and solar panel adoption.

7. CONCLUSIONS

This study explores the correlation between TOU and the adoption of solar panels and energy efficient air conditioners among residential consumers. We find that consumers in Arizona enrolled in TOU are 27% on average more likely to install solar panels. However, this study does not show a clear correlation between TOU plan and energy efficiency adoption. The possible reason might be that while it is obvious that solar panels generate most electricity during peak hours (because the solar radiation is the strongest during afternoon hours which coincide with peak hours in summer months in most TOU plans) (Ong et al., 2010; McLaren et al., 2015), it is not obvious to consumers whether energy efficiency saves the most electricity during peak hours. Although Figure 1 shows that most energy efficiency savings from retrofits on AC are correlated with TOU peak time, this information may be not salient to energy efficiency consumers and is not easily noticed by people. Another reason could be related to the "lock-in" effect. People usually have their ACs replaced after using 15 years or over and need to replace their old HVAC system (some retrofits may be possible, which could happen earlier than 15 years). This creates one additional barrier to the adoption of energy efficiency. There are some programs to incentivize consumers to replace their ACs to energy efficient ones earlier, and the subsidies motivate the consumers to enter the market faster. Entering of energy efficient AC market only after a long period of time can be seen as a type of technological "lock- in" (Unruh, 2000), where the low-carbon technologies and policies cannot change fast enough and the old technologies still dominate. Such lock-in effect could partially explain why we do not observe a significant impact of TOU pricing on energy efficient AC adoption.

The results have important implications for policymakers and utilities. First, the result that TOU is positively correlated with solar panel adoption implies that utilities could provide more information for their customers regarding the benefit of TOU for solar adopters. When government or utilities implement educational or informational programs to electric customers, they should bundle the information about the benefits from both solar and TOU, which could potentially increase the adoption of both TOU and solar panels. From cost-effectiveness perspective, combining TOU and solar in policy programs can also achieve a lower cost per additional adoption of TOU and solar. The exact welfare impacts of TOU and solar adoption is not the focus of this study. There could also be potential issues of redistribution effects from TOU that could decrease welfare (Joskow and Wolfram, 2012). But according to Train and Mehrez (1994) and Action and Mitchell (1984), the net impact of TOU on social welfare could be positive for certain TOU price designs.

Second, for energy efficiency appliances, policies or programs could be implemented to provide more information to consumers about the timing when energy savings occur. More studies are needed to show empirical evidence about the exact savings by hour of day for energy efficient appliances. With more high-frequency data available from increasing penetration of smart meters, the timing of energy savings can be accurately tracked, which helps quantify the value of energy efficiency (Boomhower and Davis, 2019; Qiu and Kahn, 2018).

ACKNOWLEDGMENTS

Funding for this research was provided by the National Science Foundation under Grant No. 1757329. We thank Janet Chee for survey data collection and Bingbing Zhou for map creation.

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APPENDIX —THEORETICAL MODEL

We develop a theoretical model to illustrate the relationship between rate plans and investment in energy efficiency and solar panels. We construct a two-period model to illustrate consumers' decision process. In period 1, a consumer decides to 1) purchase energy efficient appliances (e.g., energy star air conditioner) or 2) adopt solar panels. In period 2, she decides on how much energy service to use after the decision in the first period. For simplification, the use of energy service in period 2 is considered as the total net benefits from all future energy services. Also, we assume that one consumer can only choose an energy star conditioner or adopt a solar panel system, an assumption justified by the empirical evidence that only a small percentage (0.49%) of consumers choose both in our data.

A consumer's choice set contains two alternative choices and the status quo: energy efficient appliance (E), solar panel system (S) and the status quo choice (Q). We assume that consumers are forward looking. In period 1, the consumer chooses the energy efficient appliance (E), solar panel system (S) or stays at the status quo choice (Q), with the initial cost $c_Q = 0 < c_E < c_S$. In period 2, the consumer chooses the amount of the energy service usage, e, that needs to be used. The electricity prices during the peak hours and off-peak hours are denoted as p_p and p_o , respectively, for the TOU plan. The marginal price in flat rate group p_f is higher than the off-peak time price p_o and lower than the peak time price p_p.

Compared to the cost of installing a solar panel system, an energy efficient appliance has a lower initial cost ($c_E < c_S$).[1] We assume the electricity used from the grid after purchasing the energy efficiency appliance is $r_E e$ and electricity used after the solar panel installation is $r_S e$. Note in our context, $r_E > r_S$, which indicates, the solar panel system will save more electricity (or use less electricity) compared to the energy efficient appliance.[2]

In period 2, a consumer's net benefit equals the total benefit derived from energy service usage minus the cost of energy service usage. $b(e)$ is the benefit function. Furthermore, consumers' benefits are heterogeneous and depend on a type variable θ. We assume a continuum of consumer types distributed on the interval $\left[\underline{\theta},\overline{\theta}\right]$. As a result, a type θ consumer's benefit from energy service usage in the TOU group is[3]

$$\pi(\theta) = \theta b(e) - \left(\alpha p_p r_l e + (1-\alpha) p_o r_l e\right), l \in \{E,S\},$$

where e is the daily energy service usage; αe and $(1-\alpha)e$ are energy services used during the peak hours and off-peak hours in the TOU group, respectively. Similarly, the p_p and p_o are the electricity prices during the peak hours and off-peak hours in the TOU group.

A type θ consumer's benefit from energy service usage in the flat rate group is

$$\pi(\theta) = \theta b(e) - p_f r_l e, l \in \{E,S\}.$$

We assume a standard benefit function that has the properties $b'(e) > 0, b''(e) < 0$, so that consumer benefit increases as more energy service is used but there is decreasing marginal return. A consumer will choose the type of technology that maximizes the consumer's benefit in period 1, where the total benefit from two periods in the flat rate group can be denoted as,

$$\Pi_{l,f}(\theta) = \delta\left(\theta b(e) - p_f r_l e\right) - c_l, l \in \{E,S\}.$$

The total benefit from two periods in the TOU group can be denoted as,

1. On average, the cost of a typical AC installation ranges $4,416–$7,212 and that of a higher energy efficient air conditioner could cost approximately $1,500 more. The average cost for a 6 kW residential solar panel is about $12,642 (after tax credits) in Arizona, respectively. (Source: https://www.homeadvisor.com/cost/heating-and-cooling/install-an-ac-unit/; http://www.centralairconditionerprice.com/#Prices-by-Efficiency; http://news.energysage.com/much-solar-panels-cost-phoenix-arizona/).

2. According to Boomhower and Davis (2019), the average largest electricity savings of energy efficient ACs during peak hours is less than 0.4 kWh/household/hour based on data from California, while based on engineering calculation, the average electricity generated from a typical sized solar panel system in Phoenix could reach 3.8 kWh/household/hour (the 20-year savings is $81,083 on average) (source: http://news.energysage.com/much-solar-panels-cost-phoenix-arizona/).

3. Compared to the price difference during peak hour in the TOU group and the corresponding price in the flat rate group, the price difference during off peak hours is much smaller. We therefore ignore the off-peak hour difference in the theoretical model to focus on the major incentive factor that may lead to difference in the adoption rate between the TOU group and flat rate group.

$$\Pi_{l,t}(\theta)=\delta\Big(\theta b(e)-\big(\alpha p_p r_l e+(1-\alpha)p_o r_l e\big)\Big)-c_l, l\in\{E,S\}.$$

The parameter δ is the discount factor in the period 2. According to the first order conditions of the profit function in period 2, in the flat rate group,

$$b'\left(e_f^l\right)=\frac{p_f r_l}{\theta}, l\in\{E,S\}$$

and

$$b'\left(e_f^Q\right)=\frac{p_f}{\theta},$$

where e_f^l and e_f^Q are the optimal usage from the alternative l and status quo choice Q under the flat rate pricing, respectively. Since $b'(\cdot)$ is decreasing and $b'\left(e_f^l\right)<b'\left(e_f^Q\right)$, we can infer $e_f^l>e_f^Q$.

In the TOU group, similarly, have

$$b'\left(e_t^l\right)=\left(\alpha p_p+(1-\alpha)p_0\right)r_l/\theta, l\in\{E,S\}$$

and

$$b'\left(e_t^Q\right)=\frac{\left(\alpha p_p+(1-\alpha)p_0\right)}{\theta},$$

where e_t^l and e_t^Q are the optimal usage in the alternative l and status quo choice Q under the time of use pricing, respectively. Since $b''(\cdot)<0$ and $b'\left(e_t^l\right)<b'\left(e_t^Q\right)$, we can infer $e_t^l>e_t^Q$.

Substitute the optimal usage function into the total benefit function, we can derive the maximized benefit of choosing the energy efficient appliance or solar panel system. The maximized benefits of remaining in the status quo Q (where $r_l=1$) in the flat rate and the TOU groups are denoted as $\Pi_{Q,f}^*(\theta)$ and $\Pi_{Q,t}^*(\theta)$, respectively.

Therefore, the cutoff point to switch to alternative l (E or S) in the flat price group can be found by setting $\Pi_{l,f}^*(\theta_f)=\Pi_{Q,f}^*(\theta_f)$,[4] and we get,

$$\theta_f=\frac{p_f\left(r_l e_f^l-e_f^Q\right)+\dfrac{c_l}{\delta}}{b\left(e_f^l\right)-b\left(e_f^Q\right)}, l\in\{E,S\}.$$

If $\theta>\theta_f$, then flat rate consumers will adopt energy efficiency or solar panel. The cutoff point to switch to alternative l in the TOU group can be found by letting $\Pi_{l,t}^*(\theta_t)=\Pi_{Q,t}^*(\theta_t)$.

$$\theta_t=\frac{\left(\alpha p_p+(1-\alpha)p_0\right)\left(r_l e_f^l-e_f^Q\right)+\dfrac{c_l}{\delta}}{b\left(e_f^l\right)-b\left(e_f^Q\right)}, l\in\{E,S\}.$$

If $\theta>\theta_t$, then TOU consumers will adopt energy efficiency or solar panels. According to θ_f and θ_t, we can find $\dfrac{\partial\theta_f}{\partial c_l}=\dfrac{1}{\delta\left(b(e_f^l)-b\left(e_f^Q\right)\right)}>0$ and $\dfrac{\partial\theta_t}{\partial c_l}=\dfrac{1}{\delta\left(b(e_f^l)-b\left(e_f^Q\right)\right)}>0$, indicating a higher initial investment cost would increase the type threshold and lead to a smaller subset of consumers willing to switch. In addition, when the saving rate r_l changes, we have (note that e_f^l is a function of r_l; also note that $b'\left(e_f^l\right)=p_f r_l/\theta$)

4. Note that $\Pi_{l,f}(\theta)-\Pi_{l,t}(\theta)$ is always decreasing as θ increases.

$$\frac{\partial\theta_f}{\partial r_l} = \frac{\left(p_f r_l \frac{\partial e_f^l}{\partial r_l} + p_f e_f^l\right)\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right) - \frac{\gamma_l p_f}{\theta}\frac{\partial e_f^l}{\partial r_l}\left(p_f\left(r_l e_f^l - e_f^Q\right)+\frac{c_l}{\delta}\right)}{\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right)^2}.$$

When the above derivative evaluated at $(\theta = \theta_f)$,

$$\frac{\partial\theta_f}{\partial r_l} = \frac{p_f e_f^l}{b\left(e_f^l\right)-b\left(e_f^Q\right)} > 0,$$

as $e_f^l > e_f^Q$ and $b'(\cdot) > 0$. One can also apply the Envelop Theorem directly here to simplify the derivation process. Similarly, we can conclude that in the TOU group, who choose to remain in the status quo $(\theta = \theta_t)$

$$\frac{\partial\theta_t}{\partial r_l} = \frac{\left(\alpha p_p + (1-\alpha) p_0\right) e_f^l}{b\left(e_f^l\right)-b\left(e_f^Q\right)} > 0.$$

Therefore, we have the following proposition.

Proposition 1. *A higher initial investment cost would increase the type threshold and lead to a smaller subset of consumers willing to switch; a higher saving rate (a smaller r) leads to a larger set of consumers (a smaller θ_f) to switch away from status quo.*

Comparing θ_f and θ_t, we show that depending on the relative magnitude of p_f and the "effective" TOU price $\tilde{p} = \alpha p_p + (1-\alpha) p_0$, we can compare θ_f *and* θ_t. First, we need to see whether there exists a monotonic relationship between the function

$$\theta(\tilde{p}) = \frac{\tilde{p}\left(r_l e_f^l(\tilde{p}) - e_f^Q(\tilde{p})\right)+\frac{c_l}{\delta}}{b\left(e_f^l(\tilde{p})\right)-b\left(e_f^Q(\tilde{p})\right)}$$

and the price variable . Take the first order derivative with respect to

$$\frac{\partial\theta}{\partial\tilde{p}} = \frac{\left[\left(r_l e_f^l - e_f^Q\right)+\tilde{p}\left(r_l\frac{\partial e_f^l}{\partial\tilde{p}} - \frac{\partial e_f^Q}{\partial\tilde{p}}\right)\right]\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right)-\left(\tilde{p}\left(r_l e_f^l(\tilde{p}) - e_f^Q(\tilde{p})\right)+\frac{c_l}{\delta}\right)\left(\frac{\partial b}{\partial e_f^l}\frac{\partial e_f^l}{\partial\tilde{p}} - \frac{\partial b}{\partial e_f^Q}\frac{\partial e_f^Q}{\partial\tilde{p}}\right)}{\left(b\left(e_f^t\right)-b\left(e_f^Q\right)\right)^2}$$

$$= \frac{\left[\left(r_l e_f^l - e_f^Q\right)+\tilde{p}\left(r_l\frac{\partial e_f^l}{\partial\tilde{p}} - \frac{\partial e_f^Q}{\partial\tilde{p}}\right)\right]\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right)-\frac{\tilde{p}}{\theta}\left(\tilde{p}\left(r_l e_f^l(\tilde{p}) - e_f^Q(\tilde{p})\right)\boxplus\frac{c_l}{\delta}\right)\left(\square\gamma_l\frac{\partial e_f^l}{\partial\tilde{p}} - \frac{\partial e_f^Q}{\partial\tilde{p}}\right)}{\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right)^2}$$

$$= \frac{\left(r_l e_f^l - e_f^Q\right)\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right)+\tilde{p}\left(\square r_l\frac{\partial e_f^l}{\partial\tilde{p}} - \frac{\partial e_f^Q}{\partial\tilde{p}}\right)\left(b(e_f^l)-b(e_f^Q)-\frac{\tilde{p}}{\theta}\left(r_l e_f^l(\tilde{p}) - e_f^Q(\tilde{p})\right)\boxplus\frac{c_l}{\delta\tilde{p}}\right)}{\left(b\left(e_f^l\right)-b\left(e_f^Q\right)\right)^2}.$$

According to the definition of θ, at the cutoff point,

$$b\left(e_f^l\right)-b\left(e_f^Q\right)-\frac{\tilde{p}}{\theta}\left(r_l e_f^l(\tilde{p}) - e_f^Q(\tilde{p})+\frac{c_l}{\delta\tilde{p}}\right)=0.$$

Therefore,

$$\frac{\partial\theta}{\partial\tilde{p}} = \frac{r_l e_f^l - e_f^Q}{b\left(e_f^l\right) - b\left(e_f^Q\right)}.$$

When the rebound effect (consumers use more energy than the theoretical energy from energy efficient technologies due to lower marginal cost of using energy service) is large (i.e., $r_l e_f^l - e_f^Q > 0$), $\frac{\partial\theta}{\partial\tilde{p}} > 0$, we have $\theta_t\left(\tilde{p} = p\right) = \theta_f$, $\theta_t\left(\tilde{p} > p\right) > \theta_t\left(\tilde{p} = p\right) = \theta_f$, and $\theta_t\left(\tilde{p} < p\right) < \theta_t\left(\tilde{p} = p\right) = \theta_f$. When the rebound effect is small (i.e., $r_l e_f^l - e_f^Q < 0$), $\frac{\partial\theta}{\partial\tilde{p}} < 0$, we have $\theta_t\left(\tilde{p} = p\right) = \theta_f$, $\theta_t\left(\tilde{p} > p\right) < \theta_t\left(\tilde{p} = p\right) = \theta_f$, and $\theta_t\left(\tilde{p} < p\right) > \theta_t\left(\tilde{p} = p\right) = \theta_f$.

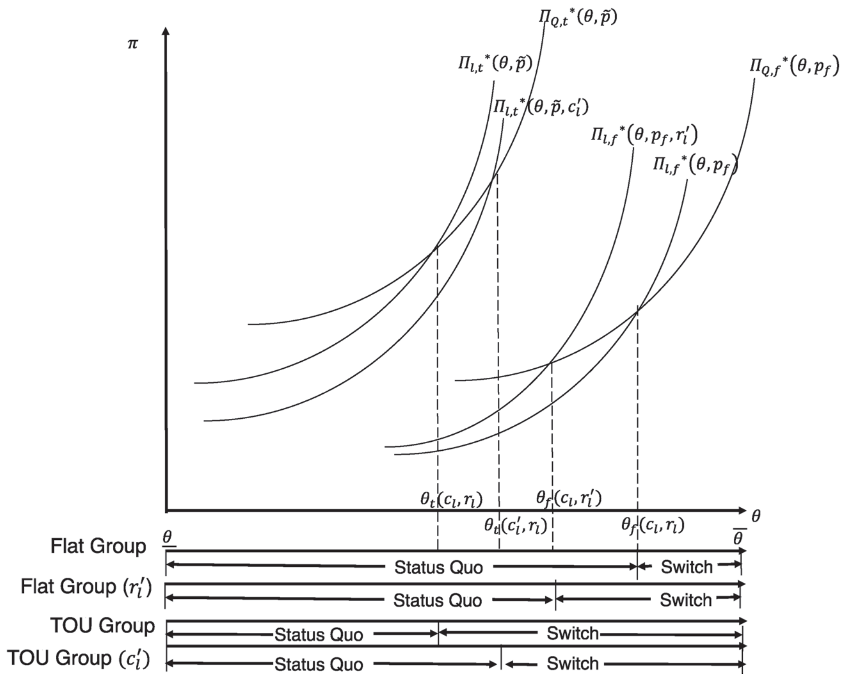
Existing literature shows that the rebound effect is very likely to be small, i.e. $r_l e_f^l - e_f^Q < 0$. Because the demand for electricity tends to be inelastic, the rebound effect is not very large and the energy efficiency measures will yield net energy savings (Gillingham, et al. 2013; Alberini, 2018).

Therefore, we have

Proposition 2. *When the rebound effect is small (or large), compared to the flat rate pricing, if the effective price $\tilde{p} > p_f$, more (or fewer) consumers in the TOU group will adopt the solar panel system or purchase the energy efficient appliance; if the effective price $\tilde{p} < p_f$, fewer (or more) consumers in the TOU group will adopt the solar panel system or purchase the energy efficient appliance.*

Figure M1 below illustrates the basic concepts, given the assumption of a reasonable small rebound effect ($r_l e_f^l - e_f^Q < 0$). The horizontal axis is the consumer's type, the vertical axis is the benefit of energy usage. Based on the above model and the SRP TOU plans, we assume $\tilde{p} > p_f$ in the figure. Threshold values under the cost c_l and saving rate r_l are denoted as $\theta\left(c_l, r_l\right)$. Figure M1 shows that when $\tilde{p} > p_f$, more consumers will buy energy efficient appliances ($l = E$) or adopt solar panel systems ($l = S$) in the TOU group compared to the flat price group. For the influence of saving rate r, a higher saving rate (a smaller r) will induce more consumers to switch away from the status quo. Using the flat rate group as an example and assuming $r_l' < r_l$, the new threshold value $\theta_f\left(c_l, r_l'\right)$ is lower than $\theta_f\left(c_l, r_l\right)$ and fewer consumers will stay at the status quo. The switching cost c_l for alternative l also influences the switching threshold. Using the TOU group as an example and assuming $c_l' > c_l$, the new threshold value $\theta_t\left(c_l', r_l\right)$ is higher than $\theta_t\left(c_l, r_l\right)$ and more consumers will stay at the status quo.

Figure M1: Theoretical framework on the impact of investment cost and saving rate on type threshold of consumers



APPENDIX A

Table A1: Interaction of TOU and peak price

	Probit model for energy efficient central AC	Probit model for energy efficient room AC	Probit model for solar panel installation
Without matching			
TOU	–0.017	0.123	–0.064
	(0.127)	(0.170)	(0.131)
TOU*peak rate	–0.029	0.033	0.442
	(0.452)	(0.616)	(0.450)
N	10,045	9,656	9,110
Pseudo R^2	0.066	0.056	0.104
Coarsened exact matching			
TOU	0.147	0.283	0.008
	(0.221)	(0.229)	(0.320)
TOU*peak rate	–0.487	–0.740	–0.095
	(0.809)	(0.820)	(1.173)
N	3,355	2,932	2,758
Pseudo R^2	0.106	0.076	0.145
Propensity score matching			
TOU	–0.009	0.112	–0.039
	(0.131)	(0.174)	(0.371)
TOU*peak rate	–0.067	0.058	0.687
	(0.467)	(0.633)	(1.355)
N	9,810	9,436	3,998
Pseudo R^2	0.076	0.117	0.159

Notes: All regressions include socio-demographics and house characteristics;
Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Adoption of energy efficiency or solar panels for owners & renters and only owners

	Owners & renters	Owners
Central AC		
Coarsened exact matching		
TOU	0.087	0.102
	(0.064)	(0.069)
N	4,039	3,233
Propensity score matching		
TOU	–0.027	0.014
	(0.042)	(0.048)
N	9,461	6,754
Solar panel		
Coarsened exact matching		
TOU	0.176*	0.256**
	(0.098)	(0.104)
N	3,200	2,550
Propensity score matching		
TOU	0.107*	0.149**
	(0.060)	(0.066)
N	8,682	5,945
Room AC		
Coarsened exact matching		
TOU	0.062	0.317
	(0.265)	(0.302)
N	256	173
Propensity score matching		
TOU	–0.137	–0.031
	(0.140)	(0.164)
N	847	544

Table A3: Adoption of energy efficiency or solar panels for internet and mail respondents

	All respondents	Internet respondents	Mail respondents
Central AC			
Coarsened exact matching			
TOU	0.087	0.061	0.078
	(0.064)	(0.076)	(0.122)
Propensity score matching			
TOU	–0.027	–0.077	–0.059
	(0.042)	(0.048)	(0.091)
Solar panel			
Coarsened exact matching			
TOU	0.176*	0.116	0.270**
	(0.098)	(0.139)	(0.135)
Propensity score matching			
TOU	0.107*	–0.0004	0.278***
	(0.060)	(0.081)	(0.094)
Room AC			
Coarsened exact matching			
TOU	0.062	2.967***	–0.600
	(0.265)	(0.893)	(0.420)
Propensity score matching			
TOU	–0.137	–0.056	–0.056
	(0.140)	(0.187)	(0.187)
Socio-demographics and home characteristics	Yes	Yes	Yes
Area (zip codes)	Yes	Yes	Yes

APPENDIX B: HETEROGENEITY BY CONSUMER/BUILDING CHARACTERISTICS

Using the sample from propensity score matching, we also examine if the probability of solar adoption conditional on TOU pricing varies across other consumer/building characteristics. The characteristics examined are monthly electricity usage, household income, square footage of the property, persons in the household, property vintage (in years), and age of household head. The specification builds on column (3) of Table 5 by introducing the interaction variable TOU*(variable of interest) into the specification. To reduce the number of combinations, we only introduce one interaction variable for each specification instead of having multiple interaction terms introduced at once. This approach also keeps the interpretation of the results relatively straight forward. The coefficients are listed in Appendix Table B1. Although each specification includes all of the variables included in column (3) of Table 5, for presentational ease we only show the coefficients of TOU and the interaction term in question. The marginal effects of TOU with 95% confidence intervals at various values of the variables of interest are shown in Figure B1.

The results show that the marginal effect of TOU on solar panel adoption probability does not vary significantly with respect to monthly electricity usage, household income, persons in household, and property vintage. In contrast, the marginal effect of TOU on solar adoption appears to decrease with square footage and increase with household age. Properties facing TOU pricing are less likely to adopt solar panels as the size of property (measured in square footage) increases. This likely reflects the fact that larger properties probably require more solar panels and hence the adoption cost becomes higher, hence lowering the probability of adoption. From a policy making perspective, increasing TOU availability (and also awareness of this availability) to smaller-size properties might achieve a higher adoption rate of solar panels.

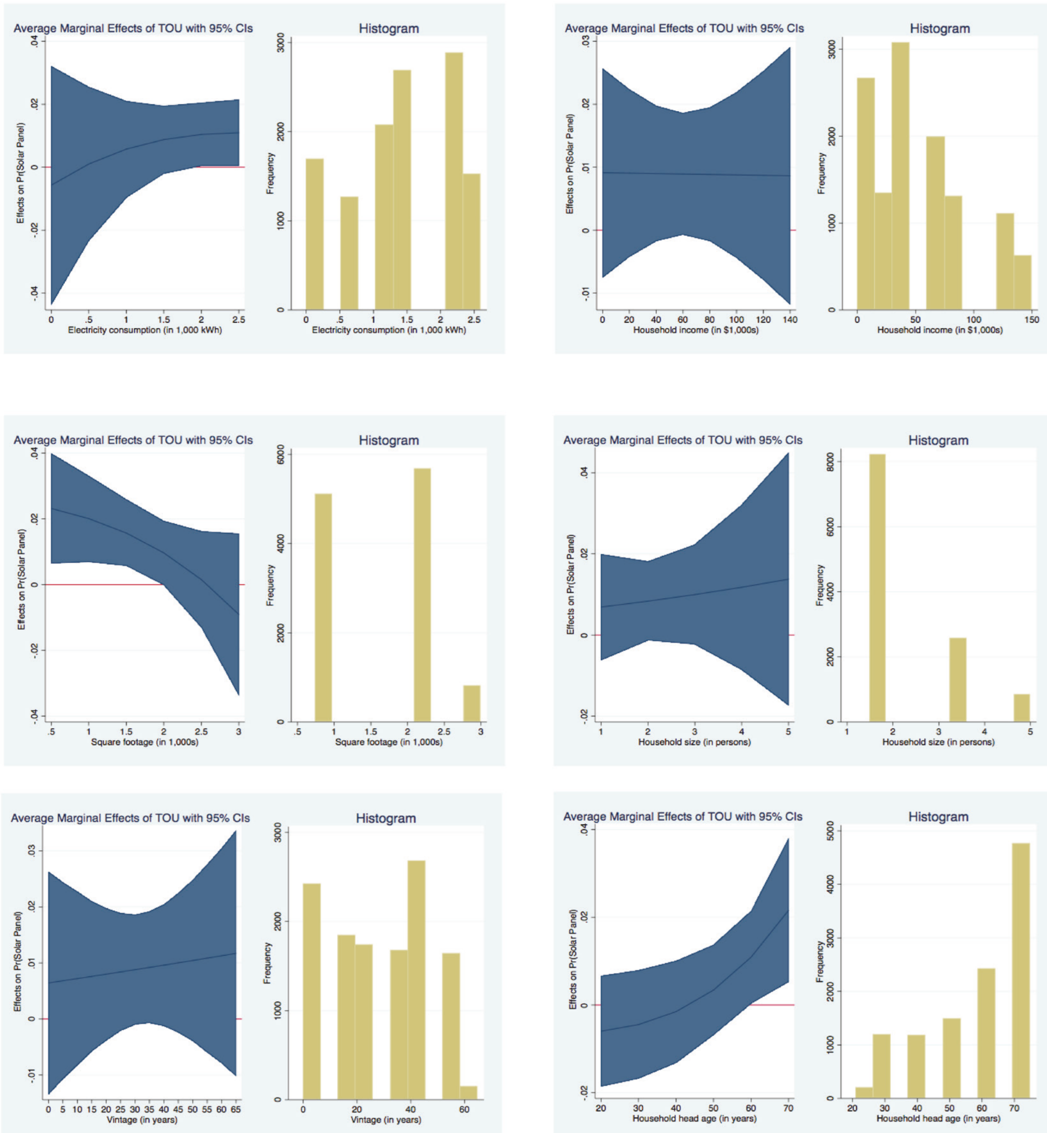
The result that older head of household who faces TOU pricing is more likely to adopt solar panels is only significant at the 10-percent level as indicated by the interaction term. There is no obvious reason why older decision makers should be more inclined to adopt solar panels when facing TOU pricing, especially when electricity usage and household income are already controlled. In light of the lack of clear economic rationalization and relatively low statistical significance, this particular result might not be too valuable for policy discussions and should be viewed with caution.

Table B1: Heterogeneity of TOU's association with solar panel adoption (using the sample from propensity score matching)

	Interaction term list					
	Monthly electricity usage (1000 kWh)	Household income ($1000)	Square footage (1000 ft^2)	Persons in household	Vintage (in years)	Age of household head
TOU	–0.037	0.111	0.516***	0.081	0.080	–0.323
	(0.123)	(0.104)	(0.180)	(0.133)	(0.126)	(0.260)
TOU* Variable of interest	0.089	–0.00006	–0.200**	0.011	0.001	0.007*
	(0.071)	(0.001)	(0.089)	(0.053)	(0.003)	(0.004)
N	8682	8682	8682	8682	8682	8682
Pseudo R^2	0.1062	0.1055	0.1079	0.1055	0.1055	0.1069
Demographics and building characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Area (zip codes)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure B1: Heterogeneity of marginal effects of TOU on solar panel installation



Notes: The variables of electricity consumption, household income, square footage, household size, vintage and household head age in the survey are asked as categorical variables indicating ranges of values.

APPENDIX C: MACHINE LEARNING

Classification and regression trees (CART)-based propensity score model is applied, which is an alternative of logistic regression to estimate propensity scores. CART-based model uses decision trees or regression trees, and has advantages over simple regressions which are sensitive to misspecification. It incorporates additionality, interaction and non-linearities (Lee et al., 2010). Boosted CART is used based on *twang* package (Ridgeway et al., 2015).

The level of interactions is two, meaning that the interaction terms of each two covariates put in the model are included. n.trees is increased from 5,000 to 10,000 to enable a larger maximum number of iterations. Two default stopping rules that use two balance metrics are applied, which are absolute standardized bias (standardized effect sizes) and Kolmogorov-Smirnov (KS) statistic. The other parameters are default. Figure C1 shows the two stopping rules consistent with each other, indicating the results are not sensitive to the stopping rule. Table C1 shows the balance table using standard effect sizes. Missing values of covariates are also balanced. Table C2 shows the results that the positive correlation still holds between solar panel installation and TOU enrollment. The coefficient on TOU is not statistically significant for the analysis of energy efficient central AC.

Figure C1: Balance measure of stopping rules

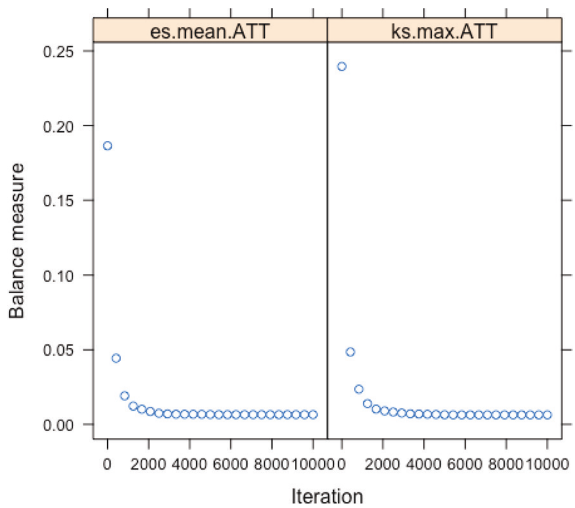


Table C1: Mean of variables before and after matching in TOU and non-TOU consumers (analysis of solar panel installation)

	Before matching				After matching			
	Non-TOU		TOU		Non-TOU		TOU	
Variable	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Ownership	7,763	0.725	4,362	0.720	7,522	0.725	4,375	0.721
		(0.446)		(0.449)		(0.447)		(0.448)
Usage	7,763	1.338	4,362	1.654	7,522	1.359	4,375	1.661
		(0.761)		(0.868)		(0.763)		(0.867)
Household income	7,763	45.341	4,362	61.310	7,522	46.124	4,375	61.381
		(40.871)		(44.969)		(41.020)		(44.908)
Square footage	7,328	1.510	4,264	1.864	7,522	1.518	4,375	1.868
		(0.795)		(0.793)		(0.795)		(0.790)
Persons in household	7,366	2.065	4,252	2.413	7,522	2.077	4,375	2.424
		(1.052)		(1.230)		(1.061)		(1.237)
White	7,256	0.751	4,124	0.746	7,522	0.755	4,375	0.746
		(0.433)		(0.435)		(0.430)		(0.435)
Stories	7,118	1.171	4,155	1.275	7,522	1.171	4,375	1.273
		(0.418)		(0.493)		(0.420)		(0.490)
Vintage	7,763	29.911	4,362	26.867	7,522	29.972	4,375	27.017
		(19.765)		(17.936)		(19.610)		(17.948)
Household head age	7,088	60.383	4,136	53.849	7,522	60.131	4,375	53.861
		(14.744)		(15.964)		(14.847)		(15.904)
Primary residence	7,454	0.898	4,291	0.976	7,522	0.898	4,375	0.976
		(0.302)		(0.154)		(0.302)		(0.154)
Swimming pool	7,677	0.156	4,346	0.401	7,522	0.159	4,375	0.401
		(0.363)		(0.490)		(0.366)		(0.490)
Dwelling type								
Mobile home	7,299	0.045	4,196	0.011	7,522	0.210	4,375	0.165
		(0.208)		(0.103)		(0.407)		(0.371)
Single family house	7,299	0.745	4,196	0.822	7,522	0.745	4,375	0.824
		(0.436)		(0.383)		(0.436)		(0.381)
Programmable thermostats	7,763	0.524	4,362	0.651	7,522	0.536	4,375	0.651
		(0.499)		(0.477)		(0.499)		(0.477)

Notes: Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table C2: Adoption of energy efficiency or solar panels using matching from classification and regression trees (CART)-based propensity score model [a]

	Solar panel installation		Energy efficient AC adoption	
TOU	0.111**	0.122*	–0.089	–0.084
	(0.052)	(0.063)	(0.082)	(0.093)
Ownership (renter=0)		0.090		–0.110
		(0.210)		(0.218)
Monthly electricity usage (1000 kWh)		–0.001***		–0.028
		(0.001)		(0.076)
Household income ($1000)		–0.001		–0.001
		(0.001)		(0.001)
Square footage (1000 ft^2)		0.154***		0.038
		(0.054)		(0.058)
Persons in household		0.056**		0.087**
		(0.027)		(0.038)
White (non-white=0)		–0.098		–0.050
		(0.083)		(0.097)
Stories		–0.031		–0.245*
		(0.073)		(0.130)
Vintage (in years)		0.001		0.008**
		(0.002)		(0.004)
Age of household head		0.010***		0.001
		(0.003)		(0.004)
Primary (seasonal residence=0)		0.520***		0.346*
		(0.176)		(0.196)
Swimming pool		0.179**		–0.011
		(0.071)		(0.122)
Dwelling type(apartment=0)				
Mobile house		–0.024		–0.483*
		(0.336)		(0.269)
Single family house		0.283		–0.485**
		(0.329)		(0.239)
Programmable thermostats		0.022		0.239**
		(0.069)		(0.107)
Constant	–1.746***	–3.174 ***	–2.232***	–2.301
	(0.041)	(0.442)	(0.060)	(0.501)

[a] Analysis of energy efficient room AC adoption is not included when machine learning is applied due to its small sample size; areas are not included due to concerns of co-linearity;
Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

APPENDIX D: CALCULATIONS FOR MONETARY VALUATION OF TOU IMPACT

Emission impact of TOU-correlated solar panel adoptions

We first calculate the number of installations correlated with TOU enrollment. The number of total SRP residential consumers is about 690,200 and 30% are on TOU pricing. Based on our findings, consumers enrolled in TOU are about 0.9-1.4 percentage points more likely to install solar panels. For simplicity, we take the mid-point of 1.2 percentage points for calculations to come. Then based on the above parameters, the total increase in solar panel adoption associated with TOU would be 690,200 *0.3*1.2 /100=2,485. We then obtain estimates of emission reductions from solar panels. We start with the hourly average electricity generation activity per installation. The annual average hourly marginal damages of different emissions (CO_2, SO_2, NO_X and particulate matter) per kWh are obtained from (Holland et al., 2016). The North American Electric Reliability Corporation (NERC) is a regulatory authority to ensure the reliability and security of the grid. It is divided into nine regions. We use the values from Western Electricity Coordinating Council (WECC) where Arizona is located. We assume that the marginal emissions factors of a unit of energy savings from all customers of a given NERC region are the same due to trading in electricity in the same region. The annual average hourly solar panel electricity generation is based on the PVWATTS model[5] for a typical 5kW system.[6] By multiplying the marginal damages and solar panel electricity generation, we can calculate the annual hourly savings from reduced emissions created by a solar panel installation. By multiplying the total increase in solar panel adoption and the savings by a solar panel installation, we get the total annual savings from solar panel installation correlated with TOU enrollment. The results are summarized in Appendix Table D1.

Table D1: Annual savings from reduced emissions by solar panel installation for by SRP consumers

		Marginal damages for emissions[a]				Annual savings from reduced emissions by all SRP TOU consumers[b]			
Hour	Output of solar generation (W)	CO_2 ($/ kWh)	SO_2($/ kWh)	NO_X($/ kWh)	PM[c] ($/ kWh)	CO_2 ($)	SO_2($)	NO_X($)	PM ($)
1	0	0.0204	0.0055	0.0021	0.0007	0	0	0	0
2	0	0.0210	0.0054	0.0021	0.0009	0	0	0	0
3	0	0.0183	0.0049	0.0020	0.0005	0	0	0	0
4	0	0.0208	0.0052	0.0022	0.0007	0	0	0	0
5	5.486	0.0207	0.0049	0.0021	0.0009	103.219	24.432	10.417	4.493
6	60.784	0.0176	0.0038	0.0018	0.0008	970.547	212.067	99.653	45.695
7	548.903	0.0148	0.0035	0.0016	0.0004	7344.126	1744.982	791.820	210.475
8	1495.810	0.0153	0.0034	0.0015	0.0005	20728.745	4645.352	2090.361	707.594
9	2345.964	0.0153	0.0036	0.0014	0.0005	32517.508	7592.369	2995.459	1092.314
10	2937.702	0.0151	0.0034	0.0014	0.0004	40268.564	8968.463	3615.680	1032.138
11	3283.802	0.0149	0.0030	0.0013	0.0004	44484.103	9003.260	3997.875	1113.234
12	3324.895	0.0148	0.0029	0.0013	0.0004	44527.549	8666.930	4008.101	1103.946
13	3149.649	0.0142	0.0027	0.0013	0.0003	40697.246	7714.232	3771.707	871.229
14	2802.403	0.0140	0.0026	0.0013	0.0003	35687.863	6589.764	3281.920	746.203
15	2173.906	0.0140	0.0024	0.0013	0.0003	27565.042	4728.404	2537.996	610.791
16	1348.279	0.0139	0.0025	0.0013	0.0003	17002.453	3057.206	1600.258	403.030
17	505.608	0.0136	0.0026	0.0013	0.0004	6222.897	1208.455	585.106	168.379
18	65.920	0.0133	0.0024	0.0012	0.0003	792.740	145.486	72.501	15.102
19	7.296	0.0132	0.0025	0.0012	0.0002	87.158	16.751	7.864	1.377
20	0	0.0140	0.0026	0.0013	0.0003	0	0	0	0
21	0	0.0149	0.0032	0.0014	0.0004	0	0	0	0
22	0	0.0167	0.0039	0.0015	0.0005	0	0	0	0
23	0	0.0181	0.0045	0.0017	0.0006	0	0	0	0
24	0	0.0198	0.0051	0.0020	0.0007	0	0	0	0
Total						318999.758	64318.153	29466.717	8126.000

[a] The average annual marginal damages for emissions in WECC are obtained from (Holland et al., 2016);
[b] The number of total SRP residential consumers is about 690,200 and 30% are on TOU rate, and based on our estimates, TOU increases the adoption by 1.2 percentage points. Then the increase in solar panel adoption due to TOU would be 690,200 *0.3*1.2 /100=2,485);
[c] PM: particulate matter.

Fiscal-subsidy equivalent of TOU impact

In this section, we conduct a back-of-the-envelope analysis to quantify what dollar amount of financial incentive would achieve the same impact on solar adoption associated with TOU pricing. To do this, we use the findings from several empirical studies that quantify the impact of solar adoption from rebates and other financial incentives. According to Hughes and Podolefsky (2015), an increase of $470 in solar incentives (from $5,600 to $6,070 per installation) increases the solar panel adoption by 10% in California; that is, an increase of $4,700 in rebates would lead to a 100%

5. http://pvwatts.nrel.gov/pvwatts.php.
6. https://news.energysage.com/much-solar-panels-cost-phoenix-arizona/.

increase in solar panel installation, assuming a constant ratio of percentage change in adoption over the dollar value of change in incentives. Similarly, according to Lasco Crago and Chernyakhovskiy (2017), approximately an increase of $5,000 per installation in the solar rebates could result in an increase of solar panel adoption by 47% in the Northeast of United States; that is, an increase of $10,638 in incentives could cause a 100% increase in adoption. Moreover, according to Gillingham and Tsvetanov (2019) an increase of $9,092 per installation leads to a 9% increase in solar panel installation in Connecticut; that is $101,022 for a 100% increase in adoption. Based on all these estimates, on average, an increase of $38,787 in incentives could lead to a 100% increase in solar panel installation.

This study finds that consumers in Arizona enrolled in TOU are associated with about 0.9–1.4 percentage point or 27% on average higher likelihood to install solar panels. The 27% is obtained using (0.9+1.4)/2/4.3, where 4.3% is the percentage of solar consumers in our sample. The 27% impact is equivalent to the impact caused by an increase of $10,472 in solar incentives ($10,472=$38,787*0.27).[7] However, since the increase in financial incentives in Gillingham and Tsvetanov (2019) is much larger than the other two studies, if we exclude this study then the equivalent amount of incentives would be $2,070 (based on (4,700+10,638)/2*0.27). Based on the above analysis, TOU is estimated to be associated with the same magnitude of impact on promoting solar adoption as an increase in financial incentives (such as rebates and tax credits) by $2,070~$10,472.

7. Note that this is a rough estimate because (1) studies of the impacts of subsidies on new adoption are few (Hughes and Podolefsky, 2015); (2) incentives can vary significantly across states and years; (3) we assume constant ratio of percentage change in adoption over the dollar value of change in incentives.