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Social Versus Private Benefits of Energy Efficiency Under Time-of-Use and Increasing Block Pricing

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Abstract

Many energy policies are implemented to subsidize the adoption of energy efficiency. However, when private benefits from energy efficiency exceed the social benefits, there is an incentive for the consumers to over-invest in energy efficiency; otherwise, there is an incentive to under-invest. This study adds to this discussion by providing an empirical estimation of the electricity savings and social benefits after energy efficiency retrofits for consumers on time-of-use (TOU) and increasing block pricing, respectively. We aim to examine how social versus private savings from a given energy efficiency measure may be different depending on different pricing plans. This study applies hourly electricity data for about 16,000 residential consumers during 2013–2017 in Arizona. We show that for the TOU consumers, the private savings from energy-efficient AC retrofits are greater than the social savings by 61%, while the increasing block rate consumers' private savings exceed the social savings by 46%, when other market failures are not considered (e.g., principal-agent problem and imperfect information). Different rate plans impose different marginal electricity prices which influence the incentives to invest in energy efficiency as well as electricity consumption behaviors that can influence both the private and social savings from energy efficiency. The result indicates that there should be potentially different levels of policy interventions towards energy efficiency for consumers on different pricing. Additionally, we also find that energy efficiency makes the electricity demand more elastic to price changes.

Keywords Energy efficiency · Time-of-use · Increasing block rate · Private benefits · Social benefits · Price elasticity

1 Introduction

It is believed that there is an "energy efficiency gap"—the failure to invest in seemingly cost-effective energy efficiency technologies (Allcott and Greenstone 2012; Gillingham and Palmer 2014). Motivated by this concern, many policies and energy efficiency programs are implemented to encourage the adoption of energy efficiency by households.

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The justifications for these policies are two folds. First, the negative externalities such as carbon emissions and environmental pollution are not internalized into the electricity prices paid by consumers (Fowlie et al. 2018). Therefore, there are social benefits associated with promoting energy efficiency. Second, there are various market failures, such as the principal-agent problems (Gillingham et al. 2012), imperfect information, and learning effects (Velthuijsen 1993; Jaffe and Stavins 1994; Gillingham and Palmer 2014; Fowlie et al. 2018). These market failures induce suboptimal investment decisions and policies can promote energy efficiency and increase investment level.

However, it is possible that consumers already have an incentive to over-invest in energy efficiency (or private benefits larger than social benefits) even when not influenced by policies to promote energy efficiency. Novan and Smith (2018) reported that there is over-investment for increasing block rate (IBR) consumers in California (other market failures are not considered). If the electricity price is higher, there is an incentive for the private to invest more. This implicit incentive to over-invest in energy efficiency can be viewed as a counter-argument to the efficiency policies.

Energy prices have an impact on investments in energy efficiency or the degrees of energy efficiency because different energy bill savings are achieved with different prices (Malatji et al. 2013). Electricity consumption behaviors will also be different under different marginal prices (Qiu et al. 2018; Faruqui and Sergici 2010). Currently, electricity prices are regulated and usually charged higher than their marginal costs. These regulated prices thus distort incentives for investment in energy efficiency (regulatory failures) (Gillingham and Palmer 2014). Existing studies have not examined how different electricity rates lead to over-investment or under-investment of energy efficiency, which is important for the quantification of the benefits of energy efficiency and also to help policymakers with the design of incentives for energy efficiency.

Dynamic pricing plans follow the cost of electricity supply more closely (Aigner et al. 1994) and help smooth the electric load profile, and therefore are often applied in the demand response programs (Torriti 2012; Vardakas et al. 2015). Among them, the time-of-use (TOU) is the most common one with higher marginal prices during peak hours and lower prices during off-peak hours (Newsham and Bowker 2010). TOU has already been widely implemented and about 30% of the consumers of Salt River Project (SRP) utility in Arizona have enrolled in TOU plans (Qiu et al. 2018). Different pricing plans (e.g., TOU vs. non-TOU pricing plan) may lead to a different amount of energy saved from a given energy efficiency measure, our study provides empirical evidence of such differences resulting from different plans.

Additionally, it is possible that consumers' price elasticity of electricity demand changes after adopting energy-efficient technologies. Energy efficiency consumers might be more price-elastic because advanced technologies such as programmable thermostats can help the consumers better respond to price changes (Faruqui et al. 2010). On the other hand, energy efficiency consumers might be less price-elastic because they do not consume much energy in the first place. Thus, empirical evidence is needed to investigate the change in price elasticities with the presence of energy efficiency, which also impacts the further estimation of the private and social savings from energy efficiency.

This study quantifies the hourly electricity savings from energy efficiency for consumers enrolled in TOU plan and compares their private and social savings with those under increasing block rate (IBR or non-TOU). Building on Novan and Smith (2018), Boomhower and Davis (2020) and others, social benefits include the following: the avoided electricity generation costs, reduced negative externality costs, deferred investments in capacity and transmission/distribution. Specifically, the research questions are as follows:

1. What is the electricity saved by hour-of-day for TOU and non-TOU consumers, respectively?
2. How do consumers' price elasticities change with the presence of energy efficiency?
3. How are the private savings on bills compared to social savings by decreasing electricity generation and pollution for TOU and non-TOU consumers, respectively?

We focus on energy-efficient air conditioning units (ACs) in Arizona by using information on energy efficiency replacements and smart metering data, which records the hourly electricity demand in kWh for about 16,000 households during 2013–2017. We attempt to use a combination of matching and fixed effects panel regression to reduce potential endogeneity, which exists since the enrollment in TOU and the adoption of energy-efficient ACs are voluntary for the consumers. Our results show that consumers under both TOU and non-TOU rates have an incentive to over-invest in energy efficiency. We also find that energy efficiency impacts the price elasticity of electricity by making the consumers more elastic to price changes.

We find that the private benefits exceed the social benefits to a lesser extent for non-TOU consumers, which implies that when there are other market failures, non-TOU consumers are more likely to under invest in energy efficiency. Therefore, energy efficiency interventions should be focused more on consumers on non-TOU price plans than those on TOU plans. However, households may not respond fully to private incentives to invest in energy efficiency due to market failures such as imperfect information and principal-agent problems (Gillingham and Palmer 2014). In this case, policy interventions such as providing better information could help with the investment in energy efficiency.

This paper proceeds as follows. Section 2 reviews the literature. Section 3 depicts a theoretical framework, describes the data and also presents the empirical strategy. Section 4 provides the econometric analysis, results and some robustness checks. The estimation of private and social savings under TOU and non-TOU is in Sect. 5. Section 6 concludes and makes some policy implications.

2 Literature Review

This study contributes to three strands of literature. First, many studies have evaluated the energy savings from energy efficiency programs (e.g., Allcott and Greenstone 2017; Fowlie et al. 2018; Liang et al. 2018); however, most of them have not examined the effect of different electricity rates on savings from energy efficiency. Different electricity rates charge prices in different ways and directly influence consumer behaviors as well as the associated savings. This study will contribute to this strand of literature by evaluating the savings under the TOU and IBR (non-TOU) rates, which have not been examined by existing studies.

Second, many studies on the evaluation of energy efficiency rely on monthly consumption with only a few exceptions (e.g., Novan and Smith 2018; Boomhower and Davis 2020) while using smart-meter electricity data[1] makes it possible to study more complex consumption behaviors (Burlig et al. 2020). The intra-day timing of electricity savings should be considered, which leads to better estimates of savings compared to those based on

[1] U.S. Department of Energy, Electric Power Annual, Released December 2017, Tables 2.1 and 10.10.

monthly or daily consumption. Moreover, the marginal environmental damages from electricity generation also differ by hour-of-day (Callaway and Fowlie 2009; Siler-Evans et al. 2012; Carson and Novan 2013; Qiu and Kahn 2018). Our study contributes to this emerging strand of the studies using high-frequency data.

Third, abundant studies have estimated the price elasticities of energy demand. The short-term price elasticities are reported to vary from 0 and -0.8 and the long-term ones are found to be between -0.3 and -1.2 (Labandeira et al. 2017; Sherwin and Azevedo 2020). Studies on the price elasticities under TOU pricing (Aigner et al. 1994; Filippini 1995, 2011; Qiu et al. 2018) showed that consumers could reduce the peak quantity demanded by shifting consumption from on-peak to off-peak hours, but the magnitudes vary. Different methods have been adopted for the estimation, including cointegration regression, the error-correction model, and Computable General Equilibrium (Hughes et al. 2008; Lijesen 2007; He et al. 2011). However, none of them have specifically explored how the price elasticities change with the presence of energy efficiency. Since price elasticity may change with energy efficiency, an empirical estimation is necessary. This study will provide an estimation of the short-run price elasticity when energy efficiency exists.

We estimate electricity savings in kWh by hour-of-day for consumers enrolled on two plans separately: (1) TOU customers with and without energy-efficient ACs; (2) IBR or non-TOU customers with and without energy-efficient ACs. This study includes both groups of consumers while paying special attention to group (1) since no existing research has specifically examined TOU consumers. The comparison of two groups helps us explore how electricity savings profiles (savings by hour-of-day) may differ under different electricity rates. We also use TOU consumers to examine the difference in elasticities due to energy efficiency. The non-TOU households cannot be used to estimate price elasticity because they face a marginal price that increases with aggregated consumption rather than a price varying intra-day.

3 Theoretical Framework, Data, and Empirical Strategy

3.1 Theoretical Framework

Figure 1 shows the theoretical framework. Figure panel (a) illustrates the conventional argument for subsidizing energy efficiency. When external cost is not priced into energy consumption, the marginal social cost of energy efficiency for a customer (as illustrated by the *MSB* curve) is larger than the marginal private benefit (as illustrated by the *MPB* curve). The marginal cost of adopting energy efficiency is illustrated by the *MC* curve. When there are no policy interventions and other market failures, the equilibrium level of energy efficiency adoption is at Q_2, which is lower than the socially optimal adoption level at Q_1. When other market failures (as illustrated by the red arrow) are present such as information asymmetry, split-incentive problem, and inattention, the private adoption level is pushed even lower. Figure panel (b) illustrates if the price of electricity paid by consumers is high enough so that the marginal private benefit is greater than the marginal social benefit, the private adoption level in the absence of other market failures could be higher than the socially optimal level. Figure panel (b) also shows that the deviation between the private adoption level and the socially optimal level could differ for customers on different pricing plans.

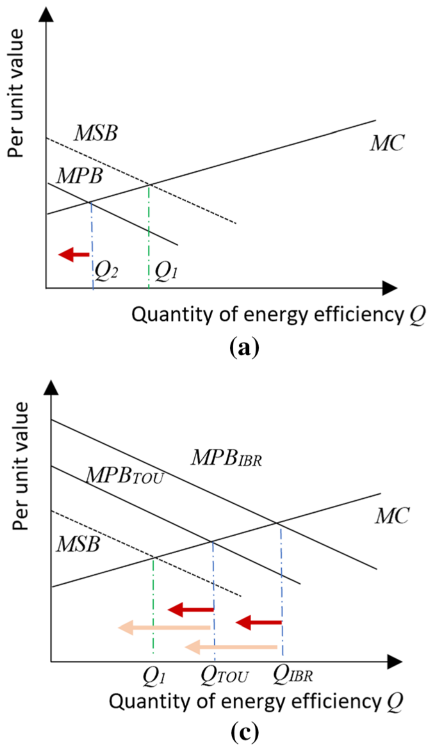

Fig. 1 Theoretical framework. *Notes*: *MSB* stands for marginal social benefit; *MPB* stands for marginal private benefit; *MC* is the marginal cost for adopting energy efficiency; the red arrows indicate the influence of other market failures such as information asymmetry, split-incentive problem, and inattention

TOU pricing and IBR pricing not only have different levels of marginal prices, but they also have different charging structures (TOU varies by peak and non-peak hours and IBR charges volumetrically based on aggregated monthly consumption). The higher the average marginal prices,[2] the larger the demand for energy efficiency, which is a "product" to reduce energy consumption.

Figure panel (c) illustrates that with other market failures and also when the marginal social benefit is smaller than the marginal private benefit, the private adoption level may be either greater (red arrow) or smaller (light red arrow) than the socially optimal level, depending on the relative sizes of the two effects. In either case, we show that the deviations between the private and socially optimal adoption levels are different for consumers on different rate plans, implying that government policies incentivizing the adoption of energy efficiency should differ by rate plans.

In the empirical analysis, we will estimate the social versus private savings under TOU and IBR, following the setting in figure panel (b), which is without other market failures. The comparison of social and private savings provides indication for the discrepancy

[2] TOU has a lower marginal price on average than the increasing block rate (IBR) in our study sample. The average marginal price for TOU consumers is $0.1005 while that for IBR consumers is $0.1218.

between the private and the socially optimal levels. If private savings are larger than the social savings, there is an incentive for consumers to over-invest. On the other hand, if the social savings are larger than the private savings, there is an incentive to under-invest and policies should subsidize energy efficiency adoption.

3.2 Data

Arizona has high temperatures during the summer and thus has large electricity consumption, which contributes to the development of dynamic pricing plans (Kirkeide 2012). Our data come from the Salt River Project (SRP), which is one of the major utilities in the Phoenix metropolitan area in Arizona. We focus on energy-efficient AC replacements in this study. The AC replacements are important since electricity consumption from ACs takes half of the peak load in Arizona (Koch-Nielsen 2013) and is also one of the end-uses that grow fastest (Boomhower and Davis 2020).

We have three datasets: two on energy-efficient AC replacements and one smart-metering data. The two separate datasets recording energy-efficient AC replacements include (1) the AC replacements from SRP's AC rebate program called "Cool Cash" which started in 2016 and (2) the Residential Equipment and Technology (RET) survey conducted in 2014. The replacements recorded by the "Cool Cash" rebate program contains detailed information including replacement date, capacity, and Seasonal Energy Efficiency Ratio (SEER). In the RET survey, the participants were selected randomly to complete the survey online or by mail. They were asked to report whether they had replaced their central AC units with more efficient Energy Star ACs during the past 3 years.[3] The rebate program provides financial incentives[4] and the financial incentives for energy-efficient ACs vary between \$200 and \$800.[5] We do not have information about the rebates for replacing the ACs in the RET survey. However, since the consumers are from the same utility company, they are likely to face the same incentives. In the main analysis, we combine the AC replacements recorded by the rebate program with the RET survey because this provides us with a larger sample. The final sample compiles the data from about 16,000 households. Altogether, we observe 1246 households with AC replacements, among which 82 (6.6%) are from the rebate program while the self-reported RET survey includes 1164 (93.4%) households. Table 5 in the "Appendix" shows the distribution of dates of replacement. Table 6 shows the technical attributes of ACs (e.g., capacity, SEER) recorded by the rebate program.

The third dataset is the customer-level smart metering data, which is also from SRP and contains hourly electricity consumption data. The smart-metering data is combined with housing characteristics (e.g., square footage, building year) and socio-demographics (e.g., household size, household income) which are obtained from the RET survey. The smart metering data spans from May 2013 to November 2017. The rebate program recorded replacements from May 2016 to April 2017 and the RET survey was submitted in July and August 2014. The timeline of the three datasets is depicted in Fig. 2. Given that the exact timing of replacements was not reported in the RET survey, we removed the electricity consumption data before their survey submission dates and only included those after

[3] Energy Star central AC unit must have a SEER that exceeds 14.

[4] The time for these incentives recorded in our dataset is from May 2016 to November 2017.

[5] The incentives given by the utility is roughly based on SEER: if $15 \leq SEER < 16$, the incentive is \$200; if $16 \leq SEER < 17$, the incentive is \$400; if $17 \leq SEER < 18$, the incentive is \$600 and if $SEER \geq 18$, the incentive is \$800. See more details in http://www.savewithsrp.com/RD/CoolCash.aspx.

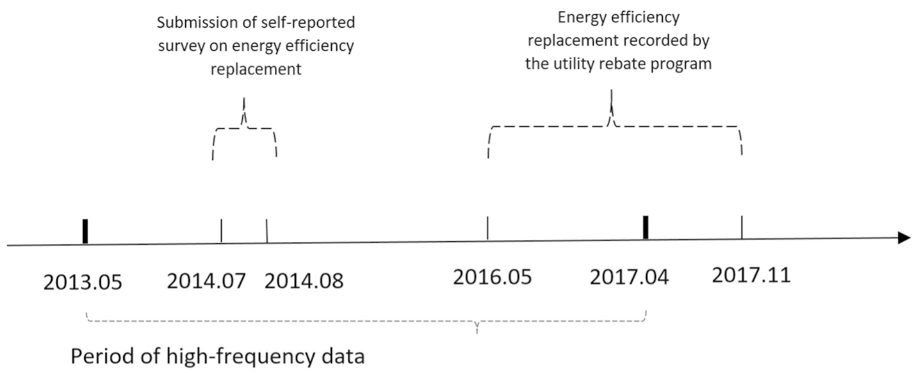

Fig. 2 Timeline of smart metering data and energy-efficient AC replacements

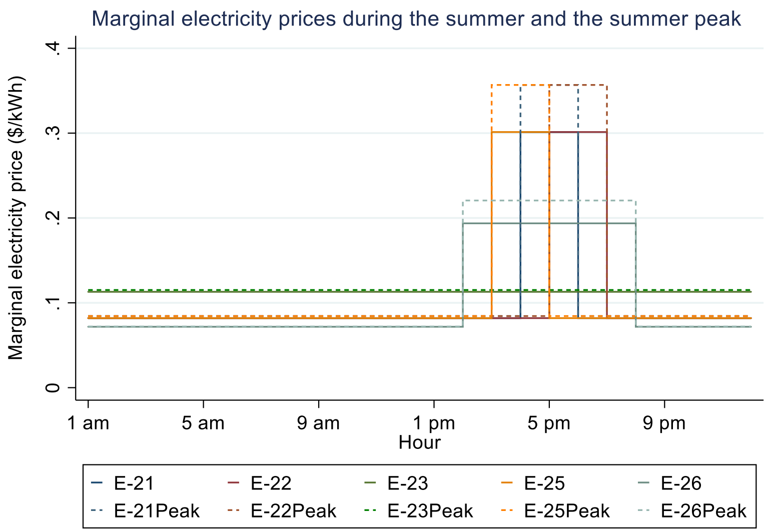

Fig. 3 The TOU and non-TOU residential electricity pricing plans. *Notes*: E-21, E-22, E-25, and E-26 are TOU plans and E-23 is non-TOU plan; E-21Peak, E-22Peak, E-25Peak, and E-26Peak are the rates in summer peak—July and August

the submission dates, namely, only the "post-treatment" observations. We also dropped 30 days prior to the known replacement date to avoid abnormal electricity usage during replacements. We dropped the accounts with multiple zip codes to ensure that changes in electricity consumption are not caused by relocation.

SRP consumers are enrolled in one of the five different electricity rate plans,[6] numbered E-21, E-22, E-23, E-25, and E-26 (Fig. 3). E-23 is an IBR with time-invariant marginal price that does not differ by hour of day. The other four plans are TOU rates with different on-peak hours and marginal prices. Table 7 gives the detailed per kWh charges for these

[6] The rates are based on the rate book issued by SRP in 2017.

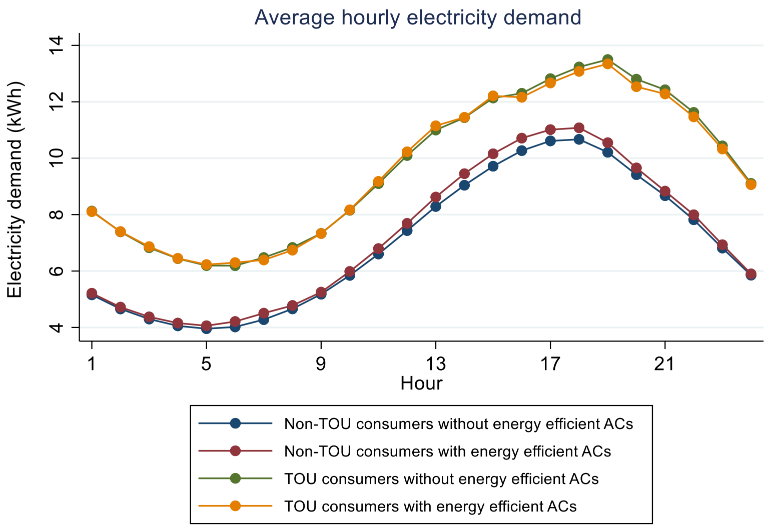

Fig. 4 Electricity demand in kWh by hour-of-day for TOU and non-TOU consumers

plans. In this paper, we only include the summer months when cooling-drive consumption may change due to AC replacements. For accounting purposes, the months of May to October are summer months, among which July and August are the peak summer months. The monthly service charge is the same for all plans and there is no demand charge.

3.3 Descriptive Statistics

Figure 4 plots the average hour-by-day electricity demand in kWh for TOU and non-TOU consumers. The average hourly demand of the TOU consumers is about 2 kWh higher than that of the non-TOU consumers. Usually, the demand peaks in the early hours of the evening when people return from work and turn on their ACs. The peak hours of the TOU consumers seem to occur 1 h later than the non-TOU consumers. The largest demand occurs at 7 p.m. for TOU consumers while at 6 p.m. for non-TOU consumers. The lowest average consumption occurs at 5 a.m. for both TOU and non-TOU consumers.

Figure 4 also shows that electricity consumption is impacted by the presence of energy efficiency. The non-TOU consumers with energy-efficient ACs tend to have higher consumption compared to those without. Also, TOU consumers without energy efficiency have slightly higher electricity consumption than that of their counterparts. Table 1 presents the summary statistics of building attributes and housing characteristics.

3.4 Empirical Strategy

There are two potential endogeneity issues. First, there could be a selection bias because the adoption of energy-efficient ACs is voluntary. For example, households that are more environmentally conscious are more likely to switch to energy-efficient ACs (Wilson and Dowlatabadi 2007; Ramos et al. 2016) and these households may also have different consumption patterns. Second, enrolment in TOU plans is not mandatory (Qiu et al. 2017)

Table 1 Descriptive statistics for the TOU and non-TOU customers with and without energy-efficient ACs

Variable	Obs.	Mean	SD	Min	Max
TOU consumers without energy-efficient ACs					
Ownership (renter = 0)	4394	0.72	0.45	0	1
Household income ($1000)	4394	61.10	45.05	0	150
Square footage (1000 ft^2)	4294	1.87	0.79	0.75	3
Household size	4283	2.42	1.23	1.5	5
White	4151	0.75	0.44	0	1
Stories	4185	1.27	0.49	1	3
Vintage	4394	26.88	17.92	0	65
Age of household head	4165	53.92	15.95	21	75
Primary (seasonal residence = 0)	4322	0.98	0.15	0	1
Swimming pool	4378	0.40	0.49	0	1
Programmable thermostats	4394	0.65	0.48	0	1
Dwelling					
Mobile home	4230	0.01	0.10	0	1
Single-family house	4230	0.82	0.38	0	1
TOU consumers with energy-efficient ACs					
Ownership (renter = 0)	496	0.84	0.37	0	1
Household income ($1000)	496	69.24	45.11	0	150
Square footage (1000 ft^2)	488	1.96	0.74	0.75	3
Household size	482	2.39	1.20	1.5	5
White	478	0.82	0.39	0	1
Stories	492	1.26	0.45	1	3
Vintage	496	27.78	15.99	0	65
Age of household head	471	55.21	13.87	21	75
Primary (seasonal residence = 0)	495	0.98	0.15	0	1
Swimming pool	496	0.45	0.50	0	1
Programmable thermostats	496	0.80	0.40	0	1
Dwelling					
Mobile home	491	0.01	0.10	0	1
Single-family house	491	0.90	0.31	0	1
Non-TOU consumers without energy-efficient ACs					
Ownership (renter = 0)	7824	0.72	0.45	0	1
Household income ($1000)	7824	45.03	40.70	0	150
Square footage (1000 ft^2)	7381	1.51	0.79	0.75	3
Household size	7422	2.07	1.06	1.5	5
White	7319	0.75	0.43	0	1
Stories	7167	1.17	0.42	1	3
Vintage	7824	29.98	19.78	0	65
Age of household head	7143	60.38	14.73	21	75
Primary residence (seasonal residence = 0)	7510	0.90	0.30	0	1
Swimming pool	7739	0.16	0.36	0	1
Programmable thermostats	7824	0.52	0.50	0	1
Dwelling					
Mobile home	7354	0.05	0.21	0	1

Table 1 (continued)

Variable	Obs.	Mean	SD	Min	Max
Single-family house	7354	0.74	0.44	0	1
Non-TOU consumers with energy-efficient ACs					
Ownership (renter = 0)	731	0.79	0.40	0	1
Household income ($1000)	731	55.84	44.08	0	150
Square footage (1000 ft^2)	723	1.62	0.78	0.75	3
Household size	712	2.15	1.08	1.5	5
White	691	0.80	0.40	0	1
Stories	715	1.12	0.35	1	3
Vintage	731	30.00	17.21	0	65
Age of household head	707	59.16	14.34	21	75
Primary residence (seasonal residence = 0)	724	0.90	0.30	0	1
Swimming pool	730	0.18	0.39	0	1
Programmable thermostats	731	0.72	0.45	0	1
Dwelling					
Mobile home	714	0.05	0.22	0	1
Single-family house	714	0.82	0.38	0	1

and consumers can switch between rate plans during billing cycles. To help address this endogeneity, we attempt to apply fixed effects to control for any confounding factors such as housing characteristics and socio-demographics that could influence enrollment in TOU plan, energy-efficient AC replacements, and also electricity consumption. A series of time fixed effects are also applied to partially control for the time-varying factors such as preference change. The analysis is conducted for TOU and non-TOU customers separately so that we can compare consumers on different plans. We dropped the households that switched between TOU and non-TOU plans (9.3% of customers) and focus only on households who stayed on the same rate plan.

We conduct propensity score matching to eliminate any systematic differences between customers with and without energy-efficient ACs. Among various algorithms that are available, we use the one with the smallest median bias, that is, the radius matching with the caliper of 0.01.[7] For a customer with an energy-efficient AC, we find a control customer with similar housing attributes and demographics but without an energy-efficient AC. Then we conduct the fixed effects regression on these matched customers. Only the households that are matched (or on the common support) are used for the statistical analysis (Fig. 10 in the "Appendix"). The matching variables include square footage, ownership, number of stories, residence type (primary or seasonal residence), dwelling type (single-family house, apartment, or mobile home), vintage, household size, race, household income, age of household head, whether there is a swimming pool, and whether the households have programmable thermostats. The balance checking of propensity score matching (Table 8), which shows that the covariates for the treated and control groups are comparable to each

[7] The different algorithms include radius matching, kernel matching, and k-nearest neighbors matching. Radius matching puts a constraint on the largest acceptable difference in propensity score when matching a control with a treated.

other after propensity score matching. Solar panel installation is not included as the covariates because our data suggests that its adoption is comparatively independent of the decision to adopt energy efficiency.[8]

We conduct several robustness checks and also combine the analysis with an innovative machine learning approach. Alternative robustness checks include the coarsened exact matching, which is another widely adopted matching approach, and adding zip code-year fixed effects, which further control for more variation across households.

4 Econometric Analysis and Results

4.1 Electricity Savings by Hour-of-Day

In this section, we estimate electricity savings by hour-of-day. The following model is applied:

$$\begin{aligned} Demand_{ihd} = \alpha_i + \sum_{h=1}^{24} \beta_1^h EE\_AC_{id} * hour\_of\_day_h + \beta_2 Price_{ihd} + \beta_3 CDD_{ihd} + \beta_4 HDD_{ihd} \\ + \beta_5 Holiday_d + \beta_6 Weekday_d + \tau_y + \delta_m + \gamma_h + \varepsilon_{ihd} \end{aligned} \tag{1}$$

where $Demand_{ihd}$ represents the electricity consumption in kWh at household i during the hour h on day d. The log of the electricity demand is not used as the dependent variable since we are interested in estimating the values of the private and social benefits, which are calculated as a marginal benefit (in \$/kWh) multiplied by the change in kWh. EE_AC refers to the status of energy-efficient AC replacements, which is equal to 1 for the treated group in their post-treatment period and is 0 all otherwise. β_1^h, the coefficient on the interaction term of energy efficiency and hour dummy, measures the hourly electricity savings and it is the one we are most interested in. The covariates include CDD (Cooling Degree Days), HDD (Heating Degree Days), holiday dummy, and weekend dummy. CDD and HDD are obtained from the hourly temperatures from the National Oceanic and Atmospheric Administration.[9] α_i is the individual-customer fixed effects and controls for the time-invariant variation among households such as square footage and household income. The time fixed effects include year fixed effects τ_y, month-of-year fixed effects δ_m, and hour-of-day fixed effects γ_h, and they capture the time-varying variation during different times such as economic development and change in local energy policies. We include all the energy-efficient AC customers in this main analysis: those recorded by the utility rebate program and also the self-reported ones.

Figure 5 plots the hourly electricity savings from the AC replacements for TOU and non-TOU consumers. The vertical axis refers to the change in hourly electricity demand (kWh), and a negative value indicates less electricity demanded (electricity savings). We find that electricity savings occur from 4 p.m. to 10 p.m. for the TOU consumers while occur throughout the day for non-TOU consumers. The largest savings happen during late afternoon and evening for all the consumers, which are usually the peak hours. This is

[8] The correlation between AC replacements and solar panel installation is −0.0685, which suggests its impact on AC replacements very weak.

[9] ftp://ftp.ncdc.noaa.gov/pub/data/uscrn/products/hourly02/.

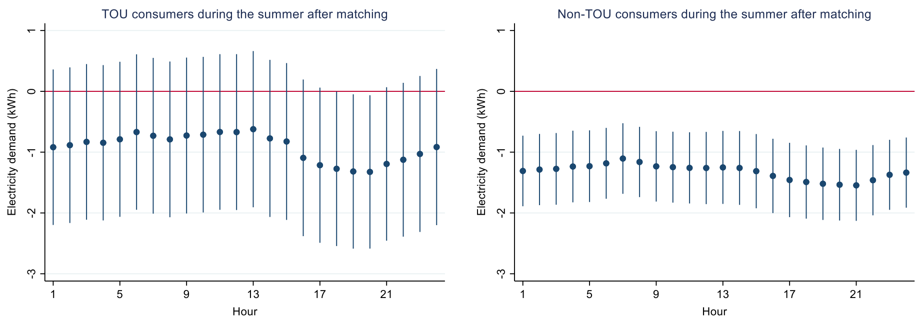

Fig. 5 Estimates of electricity savings by hour-of-day for TOU and non-TOU consumers. *Notes*: Propensity score matching is applied before the fixed effects regression. Each plot has 24 coefficients with the 95% confidence intervals. The dependent variable for regressions is hourly electricity demand in kWh. All regressions are estimated with household fixed effects and year, month-of-year, and hour-of-day fixed effects. Electricity price, CDD, HDD, holiday, and weekend are included as covariates

intuitive since the savings are larger when electricity consumption is also larger during these peak hours. The full regression results are listed in Table 9. Coarsened exact matching is also conducted ("Appendix 3") as a robustness check, which gets results generally consistent with those using propensity score matching.[10]

There are two possible reasons why TOU consumers yield different savings than non-TOU consumers.[11] Firstly, the TOU consumers have higher consumption than IBR consumers (Fig. 4), and the high-usage consumers are usually those with higher incomes.[12] The lower-income households on non-TOU plan may have less efficient electric appliances (Cayla et al. 2011), and comparatively have greater potential in saving (Liang et al. 2018). Secondly, it is also possible that houses on TOU have different electricity using behaviors (Qiu et al. 2018; Faruqui and Sergici 2010) and experience greater behavioral changes such as rebound effects. Their ACs may be set to lower temperatures after retrofits, which leads to less energy savings. This is confirmed by the finding that an IBR tariff reform in China mitigates the rebound effect (Lin and Liu 2013) and that increasing energy prices reduce the rebound effect (Ouyang et al. 2010). Hence, non-TOU households with smaller rebound effects have more savings.

The coefficients on CDD, HDD, holiday, and weekend are statistically significant, and all show expected signs. The coefficient on price for the IBR consumers is positive, which is caused by the fact that the marginal electricity price increases as consumers increase their electricity consumption.

[10] We also include the zip code-year fixed effects and control for more unobserved variation at the zip code level that also varies across years, such as infrastructure change or environmental campaign in the community. The results have a similar pattern as that of the main results. However, there are more peak hours with statistically significant savings for the TOU consumers while for the non-TOU consumers, the magnitude of savings becomes slightly larger. This suggests that slightly more zip-year level variation exists for non-TOU consumers.

[11] A formal statistical test to confirm that two groups have different savings is performed in "Appendix 4: Test the inequality of regression coefficients for TOU and non-TOU groups".

[12] Low-income households have lower consumption, as it is the case in (Fowlie et al. 2018). In this study, the average household income is \$63 k for TOU consumers while is \$50 k for non-TOU consumers. The lower-income households are not specifically the least well-off ones.

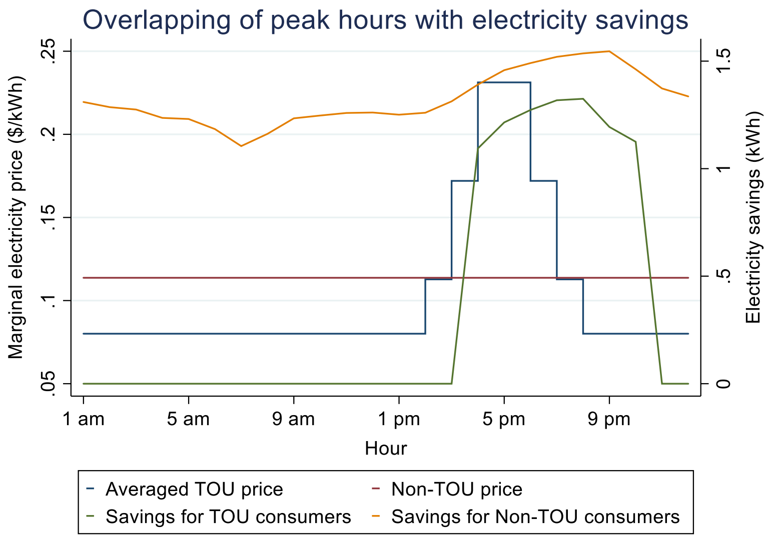

Fig. 6 Overlap of electricity savings by hour-of-day and marginal electricity prices. *Notes*: The non-TOU price is the increasing block rate (E-23) while the weighted-average electricity price for TOU consumers is the average of all the TOU prices. Point estimates are plotted. Zeros in many hours indicate that TOU consumers only save on some specific hours while savings are not found to be statistically significant at a meaningful significance level ($p < 0.10$) for other hours. A non-significant coefficient means that the null hypothesis that electricity saving is zero cannot be rejected. There may be savings for some of the households in practice, but heterogeneity may be large among them and shows insignificant savings on average. Due to the insignificance of p-values, we treat these savings in these hours as zero

4.2 Overlap of Peak Hours with Electricity Savings

Figure 6 displays how concurrently electricity savings happen with peak hours. The left axis shows the hourly marginal electricity price. The right axis shows the estimates of electricity savings taken from the regressions in the former section but formatted in positive values. The figure reveals that a correlation exists between the hours of saving and the price of electricity. The overlap is especially strong during the peak hours in the late afternoon and early evening when the marginal cost of providing electricity is also very high. This further confirms that the intra-day timing should be considered for estimation of money saved on bills because calculation using average prices and average reduction in consumption ignores a "timing premium" (Boomhower and Davis 2020). Furthermore, intra-day timing also matters for estimating environmental pollutants during electricity generation which also varies throughout the day (Sherwin and Azevedo 2020).

4.3 Heterogeneity Among Households

In this section, the heterogeneity among households is examined to investigate how the savings from AC upgrades vary across different households. The AC replacements recorded by the rebate program provide the installation time and thus for these households there are data for both pre-treatment and post-treatment periods. We run the regression in Eq. (1) individually for each treated household. Figure 7 shows the coefficients from these

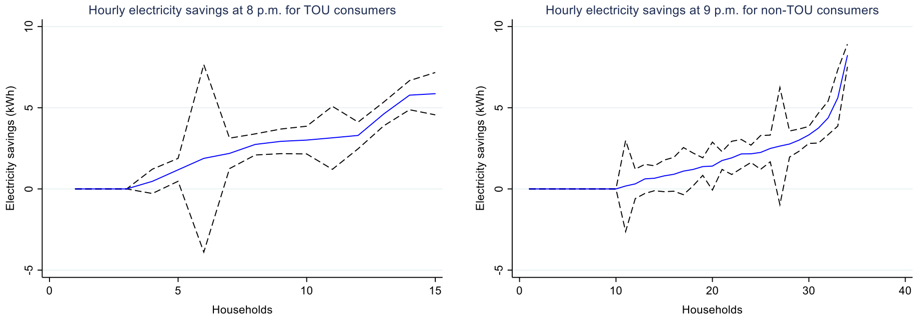

Fig. 7 Heterogeneity in hourly electricity savings among households. *Notes*: The dashed black lines show the 95% confidence intervals. All regressions are estimated with household fixed effects and time fixed effects included. Electricity price, CDD, HDD, holiday, and weekend are also included as covariates. Only 22 treated households on TOU rate and 41 on non-TOU rate recorded by the "Cool Cash" rebate program have the accurate installation dates and have both the pre-treatment and post-treatment data. After matching, the numbers further reduce to 15 for TOU consumers and 34 for non-TOU consumers (since not all households have all housing characteristics available for matching and are thus dropped

regressions at specific hours. For different TOU consumers, hourly electricity savings vary from 0 to 5.9 kWh at 8 p.m. For non-TOU consumers, hourly savings range from no savings to 8.2 kWh at 9 p.m. These hours are chosen because they are the hours when the largest electricity savings occur. The variation reveals that the savings are very heterogeneous among households and it is possible that some households have no electricity savings at all after AC replacements.

4.4 Price Elasticity

It is possible that consumers' response to electricity price changes may change with the presence of energy efficiency. In this section, we test if residential consumers will have different short-run price elasticities with the presence of energy efficiency using our large-sample hourly consumption data. We run the following model on the matched sample to examine how energy efficiency influences price elasticities.

$$\begin{aligned} Demand_{ihd} = \alpha_i + \beta_1 Price_{ihd} + \beta_2 Price_{ihd} * EE\_AC_{id} + \beta_3 CDD_{ihd} \\ + \beta_4 HDD_{ihd} + \beta_5 Holiday_d + \beta_6 Weekday_d + \tau_y + \delta_m + \gamma_h + \varepsilon_{ihd}, \end{aligned} \tag{2}$$

where β_1 implies the average change in quantity demanded when prices change without energy efficiency; β_2 is the coefficient on the interaction terms of electricity price and energy-efficient ACs and it tests whether the average price elasticities differ for consumers with the presence of energy efficiency.[13] The model is only run for the TOU consumers since the IBR consumers do not have price variation by hour-of-day.

The results (Table 2) show that the coefficient β_2 is statistically significant ($p<0.10$), which indicates that price elasticities do change with the presence of energy efficiency.

[13] All the energy-efficient AC customers are incorporated including the self-reported replacements from the RET survey.

Table 2 Estimates of price elasticities for TOU consumers with and without energy efficiency

	Coefficients
Electricity price	−12.572***
	(0.557)
Electricity price * energy-efficient AC	−2.708**
	(1.118)
CDD	0.227***
	(0.002)
HDD	0.374***
	(0.013)
Weekend	0.164***
	(0.025)
Holiday	0.037*
	(0.021)
Constant	4.101***
	(0.100)
Year fixed effects	Yes
Month-of-year fixed effects	Yes
Hour-of-day fixed effects	Yes
N	59,345,610
R^2	0.334

Propensity score matching is applied before the fixed effects regression. Standard errors in parentheses, *$p<0.10$, **$p<0.05$, ***$p<0.01$

Price elasticity is calculated to be −0.13 without energy efficiency, according to the definition formula of price elasticity.[14] This is generally consistent with the existing finding that the short-run demand for electricity is rather price-inelastic and the price elasticity is around −0.1 (Burke and Abayasekara 2018). The price elasticity with the existence of energy efficiency changes from −0.13 to −0.16 (the coefficient on the interaction term is −2.7). Although the absolute magnitude does not seem large, this equals a relatively large percentage change of 23%. This result indicates that energy-efficient technologies such as more efficient ACs make the consumers more elastic to electricity demand. Policy implications regarding this change in price elasticities are made in the last section.

4.5 Robustness Check

In this section, counterfactuals are created using a machine learning approach. Machine learning is more flexible in terms of model specification by not assuming a simple and specific relationship between variables (Varian 2014). It makes an overall prediction and creates the counterfactual; that is, the electricity consumption for the treated group supposing that they did not get treated. We use the pre-treatment data to train the model and use the trained model to predict the counterfactual for each household.

[14] Average price elasticity $= \frac{\%\Delta Quanity}{\%\Delta Price} = \frac{dQ/\bar{Q}}{dP/\bar{P}}$, where the coefficient on price gives dQ/dP, and $\bar{Q}$ and $\bar{P}$ are the average electricity quantity demanded and average price.

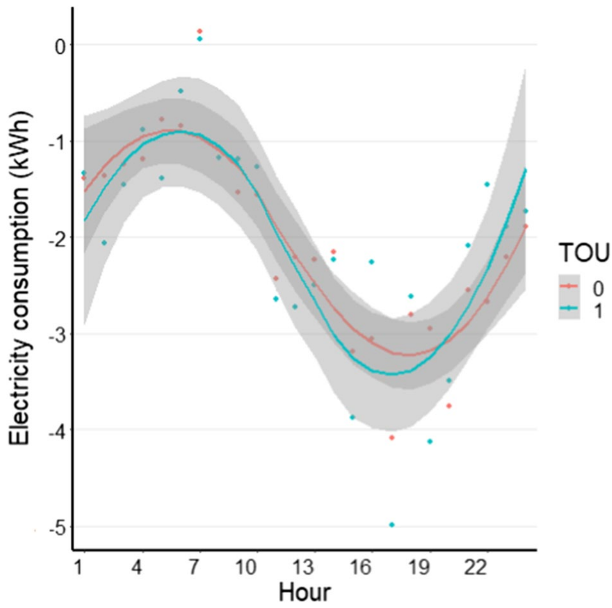

Fig. 8 Estimates of electricity savings by hour-of-day during the summer months. *Notes*: The blue line is for the TOU consumers and the red line is for the non-TOU consumers. The grey area is the 95% confidence interval with the standard error. The method for computing standard errors after model selection methods is not yet well addressed. Thus following (Prest 2020), we use an OLS regression

Following (Burlig et al. 2020), we apply the Least Absolute Shrinkage and Selection Operator (LASSO) method.[15] The assumption is that the electricity consumption of the treated group continues their pre-treatment trend. The pre-treatment data is used to get the trend and predict the consumption without absorbing impacts from the treatment. A random treatment date is assigned for the control households, and the observations before the hypothetical replacement date are used as pre-treatment data. The predictors include building attributes and socio-demographics. After the counterfactuals are created, we use a difference-in-difference strategy to get the average treatment effect. The formula is as follows:

$$\hat{\beta} = \left(y_{T,post} - \hat{y}_{T,post}\right) - \left(y_{T,pre} - \hat{y}_{T,pre}\right) - \left(y_{C,post} - \hat{y}_{C,post}\right) - \left(y_{C,pre} - \hat{y}_{C,pre}\right), \quad (3)$$

where the predicted values (noted with hats) are the prediction from the trained model. Subscript T denotes the treated group while C refers to the control group.

The results[16] (Fig. 8) show that the pattern of electricity savings is similar to the main results, but the magnitude of the estimates seem to be larger. The largest electricity savings also occur during peak hours. The variation between the largest and smallest savings tends to be larger for TOU consumers than non-TOU consumers. The possible reason might be that a machine learning approach could capture more variation across hourly consumption while the previous method attributes some of the variations to household fixed effects.

[15] Other models could also be applicable such as random forests (Cicala 2017). A LASSO is preferred if covariates are more likely to have strong linear effects on outcomes.

[16] The self-reported replacements are excluded since clear installation dates are not available for them.

Table 3 Average electricity savings from energy-efficient ACs during summer months

	TOU consumers	Non-TOU consumers
Private savings ($)	263.1	695.4
Social savings ($)	163.7	477.0
Environmental damages ($)	29.0	124.5
Generation savings ($)	64.4	146.5
Reduced capacity investments ($)	21.1	23.3
Reduced transmission/distribution cost ($)	49.2	182.7
(Private savings—social savings)/social savings	61%	46%
Social savings/private savings	62%	69%

5 Private and Social Savings

5.1 Comparison of Private Versus Social Savings

We employ hourly electricity savings and hourly prices to estimate the private and social savings. The daily private savings for an average consumer are calculated using $\sum_h \beta_1^h price_h$, where $price_h$ is the hourly price and β_1^h is the estimated hourly electricity savings. The total private savings are obtained by summing up the daily savings across all summer days.[17]

The social savings are calculated by incorporating two components: (1) reduction in environmental damages from pollutants, and (2) reduced social cost from electricity generation. We incorporate the following major pollutants: CO_2, SO_2, $NO_{X,}$ and particulate matter. The daily environmental damages are calculated by $\sum_h \beta_1^h MD_h$, where β_1^h is the hourly electricity savings, and the hourly marginal damage factors MD_h are obtained from (Holland et al. 2016). We apply the set of marginal damage factors from the Western Electricity Coordinating Council (WECC) region which Arizona belongs to. Some electricity is lost during the generation (4.6%) and transmission/distribution process (9.6%) (Graff Zivin et al. 2014; Novan and Smith 2018), so two adjustments are made by scaling up the social savings by 1.05×1.096.

The reduced social cost from electricity generation is estimated using the hourly system lambdas reported in the FERC 714 forms.[18] The system lambda is the system marginal cost,[19] which is usually calculated to minimize production costs among different production resources. We use system lambdas to indicate the economic marginal cost of generation. Besides, deferred capital investment in generation capacity is estimated by multiplying the largest average hourly changes in summer consumption by the average monthly cost of capacity. An average monthly capacity cost of $2.66/kW is adopted following

[17] The implied payback period is estimated to be 15.4 years for the TOU consumers and 5.0 years for the non-TOU consumers, depending on the size of their annual savings. The cost of energy-efficient AC replacement is assumed to be $5000. The details are seen in Table 10 in "Appendix 1".

[18] https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data.

[19] https://www.e-education.psu.edu/eme801/node/532.

Table 4 Average electricity savings from energy-efficient AC using alternative marginal factors

	TOU consumers	Non-TOU consumers
Private savings ($)	263.1	695.4
Social savings ($)	182.1	527.3
Environmental damages ($)	47.4	174.8
Generation savings ($)	64.4	146.5
Reduced capacity investments ($)	21.1	23.3
Reduced transmission/distribution cost ($)	49.2	182.7
(Private savings—social savings)/social savings	44%	32%
Social savings/private savings	69%	76%

(Novan and Smith 2018). We also included the deferments in transmission/distribution investments. According to eia.gov,[20] the average electricity delivery cost is estimated to be 3.2 cents/kWh (in 2016), including the costs of transmission infrastructure, distribution equipment, installation, equipment maintenance, customer billing, education, relations, labor costs, and others. The avoided transmission and distribution costs are calculated by multiplying the average delivery cost by the total decreased consumption.

We find that the TOU consumers with energy efficiency save $263 on electricity bills (Table 3) while the non-TOU consumers have higher private savings at $695. For both TOU and non-TOU consumers, the total social savings are smaller than the private savings. This suggests that there is an incentive to over-invest in energy efficiency for both types of consumers (when not considering other market failures). For the non-TOU consumers, the private savings exceed the social savings by 46% while for the TOU consumers, the private savings are greater than the social savings by 61%. The discrepancy between social and private savings is larger for TOU consumers than non-TOU consumers.

This result is consistent with that of (Novan and Smith 2018) which also finds the private savings are larger than the social savings for consumers in California where the households also face tiered tariffs larger than the social marginal cost and the households have incentives to overinvest in energy efficiency. The results are also in line with the theoretical framework that TOU and IBR impose different marginal prices which influence the incentives to invest in energy efficiency as well as electricity using behaviors that influence both the private and social savings. The TOU plan results in lower demand for energy efficiency (the absolute value of the private savings is lower) with a lower marginal price compared to the IBR plan in our sample.

We also tried an alternative set of the marginal damage factors, following (Azevedo et al. 2017).[21] Compared to the previous set of factors, the alternative factors are larger for CO_2, NO_X and particulate matter while the factor for SO_2 is smaller. This alternative factor set also has separated different seasons and we use factors for the summer season. The results (Table 4) show that for TOU consumers, the private savings are larger than the social savings by 44% while for non-TOU consumers, the private savings exceed the social

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

[21] https://cedm.shinyapps.io/MarginalFactors/.

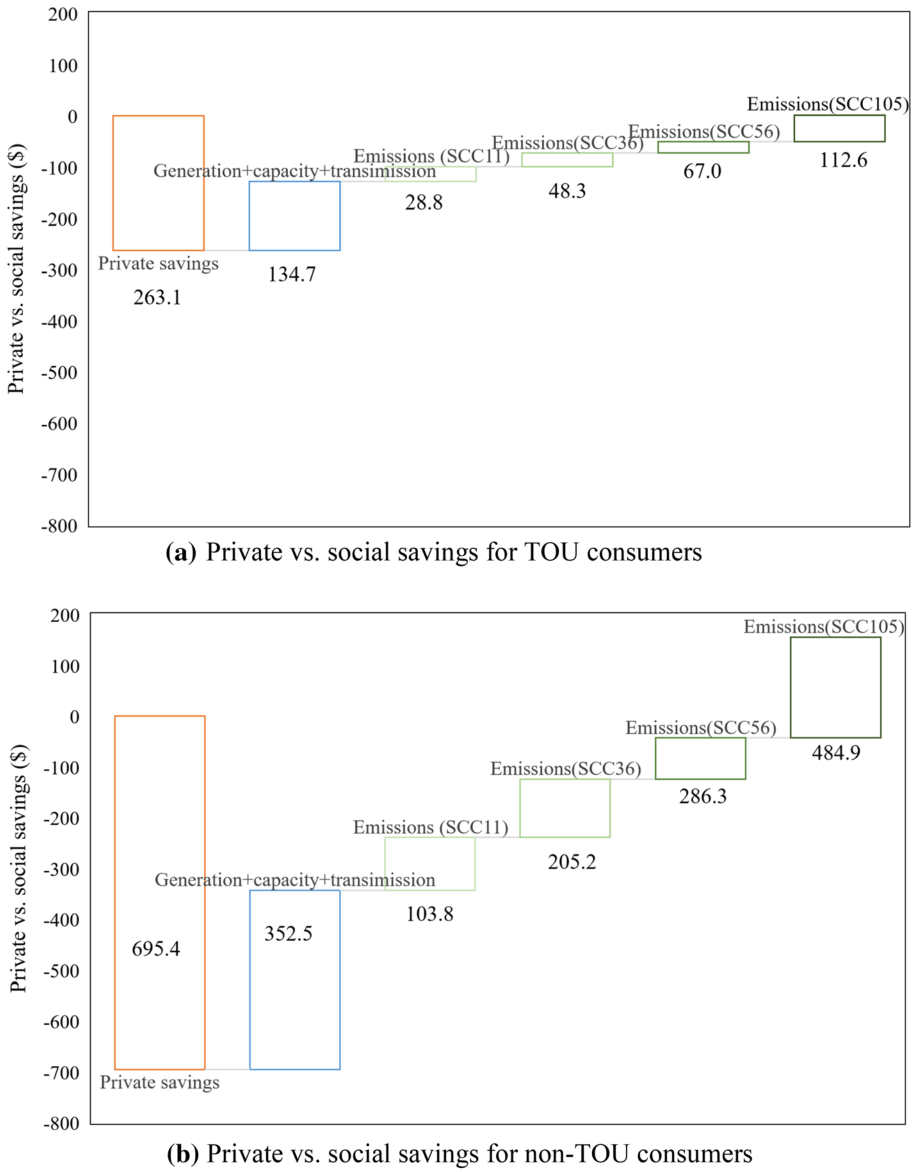

Fig. 9 The comparison of private versus social savings under different scenarios. *Notes:* The savings on the vertical axis is formatted negative for the ease of comparison. If the sum is zero for all bars, the social savings are equal to the private savings

savings by 32%. Again, the TOU plan yields a slightly larger deviation between private and social savings in comparison to the non-TOU plan.

5.2 Scenario Analysis

The social cost of carbon (SC-CO_2 or more simplified SCC) is assumed to be at \$35 for a metric ton of carbon dioxide emissions during the calculation of environmental damages in the last section. However, there is large uncertainty for the long-term damages from carbon dioxide (Tol 2005). Considering this uncertainty, we use a scenario analysis with alternative SCC values: \$11, \$36, \$56 and \$105, which are estimated by the Environment Protection Agency (EPA). The first three values are estimated at the discount rate of 2.5%, 3%, and 5%, while the fourth is the lower-probability but higher-impact outcome with particularly harmful impacts (EPA 2016).

In the four scenarios, the estimation of social savings depends on the SCC values and a larger SCC yields larger social savings. However, the private savings are always larger than the social savings with all the alternative SCC values for TOU consumers while for non-TOU consumers, the social savings are larger than the private savings only when \$105 is employed as the SCC (Fig. 9). Therefore, our main findings remained, which is that the private savings are larger than the social savings and the deviation between them is larger for TOU consumers than non-TOU consumers.

5.3 Discussion

Investments in energy efficiency are voluntary for consumers. Although this study matches the households on most important observable characteristics (socio-demographics and housing characteristics), some heterogeneity remains with time-varying unobserved variables at the individual-consumer level not well controlled for, such as consumers' varying preferences (Nair et al. 2010), the learning effect (Jessoe and Rapson 2014), and new information (Shen and Saijo 2009). This remaining endogeneity could potentially lead to biased estimates. Here, we provide additional evidence that the potential time-variant individual-specific unobservables do not pose a big threat to our estimates. We conducted a graphical event study analysis, which shows that the treated and the control groups maintain a parallel trend before the treatment. There is no statistically significant difference in the trends between the treated and control groups prior to the energy efficiency replacement. This indicates that the parallel trend assumption is satisfied (Fig. 11). The results are generally consistent with our main analysis. Based on our analysis, the non-TOU consumers have reduced electricity consumption after the replacement; however, the TOU consumers do not seem to have reduced consumption. This may be due to the possibility that savings only occur during specific hours for TOU consumers and average hourly savings are not obvious (Fig. 5).

This study finds that both TOU and non-TOU consumers have incentives to over-invest (private savings larger than social savings) while over-investment is larger for TOU consumers. The estimation of private and social benefits does not account for other market failures, as mapped in Fig. 1b. The existence of additional market failures could reduce investments in energy efficiency. If the effect of the other market failures is large enough, the private benefits could become smaller than the social benefits and our conclusion of over-investment will not hold.

As indicated in Sect. 3.2, we were not able to gather complete data from all the households we study. The number of treated households with accurate installation dates (those recorded by the rebate program) is only 49 (15 TOU consumers and 34 non-TOU consumers). Most households are without accurate installation dates (those recorded by the RET survey). Thus, the source of variation in our main analysis comes mainly from the comparison between the treated and the control groups.

6 Conclusion and Policy Implications

This study provides an empirical assessment of the effects of two different pricing plans on electricity savings from energy-efficient AC replacements for residential buildings. Using a rich dataset of hourly electricity consumption of about 16,000 consumers from 2013 to 2017 in Arizona, we estimate the hour-of-day electricity savings and then use the estimated hourly savings to estimate their private and social benefits. We show that for the TOU consumers, the private savings are greater than the social savings (other market failures not considered), while for non-TOU consumers, the private savings also exceed the social savings, but by a lower percentage. In addition, we find that energy efficiency makes the electricity demand more elastic to price changes, suggesting energy technologies help the consumers better respond to price changes.

Our results have important policy implications. First, to address the market failure of negative externalities of energy consumption, many existing policies are implemented to incentivize energy efficiency rather than tax carbon emissions directly (Allcott and Greenstone 2017). These policies potentially lead to a discrepancy between social and private savings, resulting in either over-investment or under-investment of energy efficiency. Our results show that (when other market failures are not considered) the private benefits of non-TOU consumers exceed the social benefits to a lesser extent. This indicates non-TOU consumers are more likely to underinvest in energy efficiency than the TOU consumers. Therefore, one policy implication is that energy efficiency should target consumers on non-TOU plan than those on TOU plan. Larger incentives should be provided to non-TOU consumers who are less likely to over-invest in energy efficiency.

Second, this study finds that energy efficiency makes consumers more elastic, indicating that energy efficiency could help ease the burden on the utility companies in terms of balancing the load and generation. It is expensive for utilities to maintain the generation capacity for peak loads and also to ensure supply stability. Consumers' increased response to price changes helps utilities better reduce the peak load. Our results show that price elasticity changes with the presence of energy efficiency. This finding highlights the importance of an empirical estimate of the savings from energy efficiency. It is also of significance for future exploration of how revenues of utilities would change with the increasing penetration of energy efficiency among households. Besides, this finding implies that a load response program through pricing can be implemented together with energy efficiency given that energy efficiency positively impacts TOU consumers' response to price changes.

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Appendix 1

See Tables 5, 6, 7, 8, 9 and 10.

Table 5 Years of adoption for energy-efficient AC replacements

Year	Freq.	Percent
Before or in 2014[a]	1164	89.88
2016	61	4.71
2017	70	5.41
Total	1295	100

[a]The consumers in the self-reported RET survey do not have information on installation dates

Table 6 Technical attributes of energy-efficient AC replacements recorded by the rebate program

Variable	Obs	Mean	SD	Min	Max
SEER of old ACs	73	10.137	1.619	6	13
Capacity	126	43,211.9	8850.398	23,400	58,500
SEER of energy-efficient ACs	126	16.353	1.277	15	23.5
Retrofit type (unitary air conditioner = 1; unitary heat pump = 0)	126	0.532	0.501	0	1

The consumers in the self-reported RET survey do not have information on technique attributes; in this table, capacity refers to the cooling capacity of an air conditioner, which is similar to horsepower and describes how powerful the unit is in British thermal unit (BTU); SEER (Seasonal Energy Efficiency Ratio) is the ratio of cooling capacity in BTU to the energy consumed in watt-hours and higher SEER indicates being more energy-efficient

Table 7 Residential tariffs of TOU and increasing block rate in Salt River Project

Pricing plan	Name	Division	Summer rates	Summer peak rates	Notes
E-21	Price plan for residential super peak time-of-use service	On-peak	$0.3013	$0.3568	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	
E-22	Experimental plan for residential super peak time-of-use service	On-peak	$0.3013	$0.3568	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	
E-23	Standard price plan for residential service (non-TOU)	$\leq$700 kWh	$0.1082	$0.1148	–
		701–2000 kWh	$0.1101	$0.1160	
		All additional kWh	$0.1206	$0.1311	
E-25	Experimental plan for residential super peak time-of-use service	On-peak	$0.3013	$0.3568	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	
E-26	Standard price plan for residential time-of-use service	On-peak	$0.1937	$0.2206	Summer on-peak hours consist of those hours from 1 p.m. to 8 p.m
		Off-peak	$0.0718	$0.0721	

Table 8 Mean of variables before and after propensity score matching for TOU and non-TOU consumers (treatment: energy-efficient AC replacement)

Variables	Before matching				After matching			
	Control		Treated		Control		Treated	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
TOU consumers								
Ownership (renter = 0)	4394	0.72	496	0.84	3660	0.84	425	0.83
		(0.45)		(0.37)		(0.37)		(0.37)
Household income ($1000)	4394	61.10	496	69.24	3660	70.63	425	70.14
		(45.05)		(45.11)		(45.31)		(43.34)
Square footage (1000 ft^2)	4294	1.87	488	1.96	3660	1.98	425	1.98
		(0.79)		(0.74)		(0.74)		(0.73)
Household size	4283	2.42	482	2.39	3660	2.43	425	2.44
		(1.23)		(1.20)		(1.24)		(1.22)
White	4151	0.75	478	0.82	3660	0.82	425	0.82
		(0.44)		(0.39)		(0.39)		(0.39)
Stories	4185	1.27	492	1.26	3660	1.26	425	1.26
		(0.49)		(0.45)		(0.48)		(0.45)
Vintage	4394	26.88	496	27.78	3660	28.47	425	28.12
		(17.92)		(15.99)		(16.80)		(15.78)
Household head age	4165	53.92	471	55.21	3660	55.11	425	54.78
		(15.95)		(13.87)		(15.04)		(13.78)
Primary residence (seasonal residence = 0)	4322	0.98	495	0.98	3660	0.98	425	0.98
		(0.15)		(0.15)		(0.13)		(0.13)
Swimming pool	4378	0.40	496	0.45	3660	0.46	425	0.46
		(0.49)		(0.50)		(0.50)		(0.50)
Programmable thermostats	4394	0.65	496	0.80	3660	0.79	425	0.80
		(0.48)		(0.40)		(0.41)		(0.40)
Single-family house	4230	0.82	491	0.90	3660	0.90	425	0.89
		(0.38)		(0.31)		(0.30)		(0.31)
Non-TOU consumers								
Ownership (renter = 0)	5823	0.71	631	0.79	5745	0.78	600	0.78
		(0.45)		(0.41)		(0.41)		(0.41)
Household income ($1000)	5823	51.52	631	59.89	5745	56.21	600	56.33
		(40.39)		(43.61)		(41.35)		(41.32)
Square footage (1000 ft^2)	5823	1.51	631	1.63	5745	1.60	600	1.61
Household size		(0.79)		(0.78)		(0.79)		(0.78)
	5823	2.09	631	2.15	5745	2.12	600	2.14
		(1.06)		(1.08)		(1.09)		(1.08)
White	5823	0.77	631	0.82	5745	0.81	600	0.81
		(0.42)		(0.39)		(0.40)		(0.39)
Stories	5823	1.18	631	1.12	5745	1.13	600	1.13
		(0.43)		(0.35)		(0.35)		(0.35)
Vintage	5823	30.36	631	29.77	5745	30.43	600	30.28
		(19.28)		(17.02)		(18.77)		(17.09)

Table 8 (continued)

Variables	Before matching				After matching			
	Control		Treated		Control		Treated	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Household head age	5823	59.14	631	58.75	5745	59.30	600	59.10
		(15.16)		(14.44)		(14.59)		(14.48)
Primary residence (seasonal residence = 0)	5823	0.90	631	0.91	5745	0.90	600	0.91
		(0.29)		(0.29)		(0.30)		(0.29)
Swimming pool	5823	0.16	631	0.19	5745	0.19	600	0.18
		(0.37)		(0.40)		(0.39)		(0.38)
Programmable thermostats	5823	0.52	631	0.71	5745	0.70	600	0.70
		(0.50)		(0.45)		(0.46)		(0.46)
Single-family house	5823	0.74	631	0.82	5745	0.82	600	0.82
		(0.44)		(0.38)		(0.39)		(0.39)

Table 9 Electricity savings by hour-of-day from energy-efficient ACs for TOU and non-TOU consumers

Variables	TOU consumers	Non-TOU consumers
Hour 1* energy-efficient AC	− 0.919	− 1.310***
	(0.652)	(0.296)
Hour 2* energy-efficient AC	− 0.886	− 1.286***
	(0.653)	(0.299)
Hour 3* energy-efficient AC	− 0.832	− 1.275***
	(0.653)	(0.301)
Hour 4* energy-efficient AC	− 0.846	− 1.236***
	(0.651)	(0.301)
Hour 5* energy-efficient AC	− 0.789	− 1.231***
	(0.650)	(0.301)
Hour 6* energy-efficient AC	− 0.670	− 1.184***
	(0.652)	(0.297)
Hour 7* energy-efficient AC	− 0.731	− 1.105***
	(0.653)	(0.296)
Hour 8* energy-efficient AC	− 0.790	− 1.162***
	(0.653)	(0.295)
Hour 9* energy-efficient AC	− 0.727	− 1.234***
	(0.654)	(0.295)
Hour 10* energy-efficient AC	− 0.713	− 1.247***
	(0.652)	(0.297)
Hour 11* energy-efficient AC	− 0.668	− 1.259***
	(0.653)	(0.299)
Hour 12* energy-efficient AC	− 0.670	− 1.261***
	(0.654)	(0.303)
Hour 13* energy-efficient AC	− 0.622	− 1.251***
	(0.655)	(0.306)
Hour 14* energy-efficient AC	− 0.774	− 1.260***
	(0.659)	(0.310)
Hour 15* energy-efficient AC	− 0.825	− 1.313***
	(0.658)	(0.311)
Hour 16* energy-efficient AC	− 1.094*	− 1.391***
	(0.657)	(0.312)
Hour 17* energy-efficient AC	− 1.215*	− 1.458***
	(0.651)	(0.312)
Hour 18* energy-efficient AC	− 1.273**	− 1.491***
	(0.648)	(0.307)
Hour 19* energy-efficient AC	− 1.318**	− 1.520***
	(0.647)	(0.304)
Hour 20* energy-efficient AC	− 1.325**	− 1.536***
	(0.643)	(0.300)
Hour 21* energy-efficient AC	− 1.194*	− 1.546***
	(0.644)	(0.298)
Hour 22* energy-efficient AC	− 1.125*	− 1.462***
	(0.645)	(0.295)

Table 9 (continued)

Variables	TOU consumers	Non-TOU consumers
Hour 23* energy-efficient AC	−1.030	−1.373***
	(0.654)	(0.294)
Hour 24* energy-efficient AC	−0.916	−1.336***
	(0.655)	(0.294)
CDD	0.227***	0.176***
	(0.002)	(0.002)
HDD	0.375***	0.314***
	(0.013)	(0.030)
Electricity price	−13.572***	11.981***
	(0.553)	(1.103)
Weekend	0.163***	0.232***
	(0.025)	(0.010)
Holiday	0.036*	0.066***
	(0.021)	(0.016)
Constant	4.435***	0.062
	(0.268)	(0.165)
Year fixed effects	Yes	Yes
Month-of-year fixed effects	Yes	Yes
Hour-of-day fixed effects	Yes	Yes
Individual-customer fixed effects	Yes	Yes
N	59,345,610	95,636,736
R^2	0.334	0.391

The summer months are from May to October. The Standard errors in parentheses, $*p<0.10$, $**p<0.05$, $***p<0.01$

Table 10 Cost-effectiveness of energy-efficient ACs

	TOU consumers	Non-TOU consumers
Annual dollar savings ($)	411.1	1093.3
Payback period	12.2 years	4.6 years
Discounted payback period (discount rate = 3%)	15.4 years	5.0 years
Internal rate of return (per year)	14.96%	26.22%

Winter electricity savings are calculated based on the percentage of savings in the summer. The estimate of the cost of energy-efficient AC replacement is from sources: https://www.remodelingexpense.com/costs/cost-of-energy-efficient-air-conditioners/; https://www.homeadvisor.com/cost/heating-and-cooling/install-an-ac-unit/#14and16seer

Appendix 2

See Figs. 10 and 11.

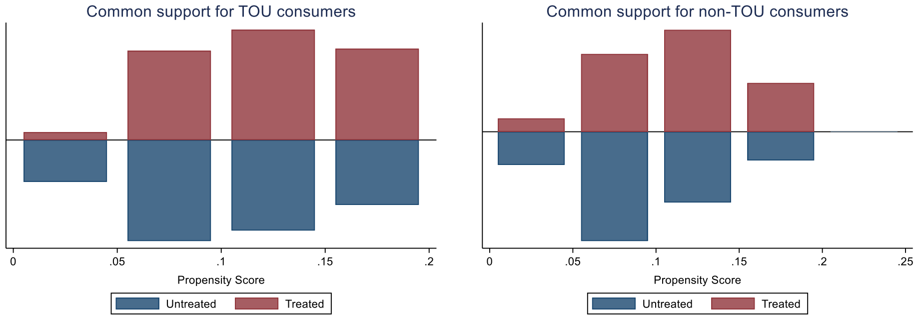

Fig. 10 Common support of propensity score matching for the TOU and non-TOU consumers

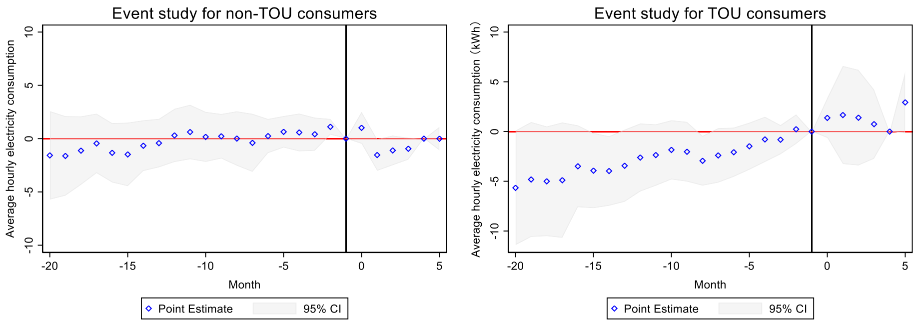

Fig. 11 Test of the parallel trend assumption. *Notes:* This plot includes the estimated coefficients and 95% confidence intervals. Time is normalized relative to the energy efficiency adoption month. Observations before $t = -20$ are dropped. Price, CDD, and HDD are included as covariates. The regression includes household fixed effects and year fixed effects. Standard errors are clustered at the household level

Appendix 3: Coarsened Exact Matching

We also match the treated and control groups using coarsened exact matching, which is widely used in more recent studies (Stuart 2010). Coarsened exact matching divides the variables into different strata and then the treated and control groups are matched based on the strata (Iacus et al. 2012). Coarsened exact matching tries to reduce the overall imbalance. 430 out of 496 (87%) TOU consumers and 641 out of 731 (88%) non-TOU consumers with energy-efficient ACs are matched. The balance checking of the covariates is shown in Table 11, which indicates that the covariates are balanced between the control and treated groups after matching.

The results (Fig. 12) obtained using coarsened exact matching are in general consistent with those using propensity score matching. For TOU consumers, the largest hourly savings also occur at 8 p.m., but there are fewer significant estimates in the later afternoon and early evening hours, while for the non-TOU consumers, the hourly savings show a similar pattern as those using propensity score matching; however, they seem to have a slightly smaller magnitude. The hourly savings for morning hours such as 8 a.m. and 9 a.m. become larger than previous results

Table 11 Mean of variables before and after coarsened exact matching for TOU and non-TOU consumers (treatment: energy-efficient AC replacement)

Variable	Before matching				After matching			
	Without energy-efficient AC		With energy-efficient AC		Without energy-efficient AC		With energy-efficient AC	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
TOU consumers								
Ownership (renter = 0)	2202	0.72	496	0.84	930	0.87	382	0.87
		(0.45)		(0.37)		(0.33)		(0.33)
Household income ($1000)	2202	0.51	496	0.64	930	0.67	382	0.67
		(0.50)		(0.48)		(0.47)		(0.47)
Square footage (1000 ft^2)	2202	0.71	496	0.75	930	0.78	382	0.78
		(0.46)		(0.43)		(0.41)		(0.41)
Household size	2202	1.00	496	1.00	930	1.00	382	1.00
		(0.00)		(0.00)		(0.00)		(0.00)
White	2075	0.75	478	0.82	921	0.86	376	0.86
		(0.43)		(0.39)		(0.35)		(0.35)
Stories	2202	0.29	496	0.26	930	0.23	382	0.23
		(0.46)		(0.44)		(0.42)		(0.42)
Vintage	2202	0.45	496	0.42	930	0.39	382	0.39
		(0.50)		(0.49)		(0.49)		(0.49)
Household head age	2094	53.92	471	55.21	914	55.53	372	55.53
		(16.06)		(13.87)		(13.52)		(13.53)
Primary (seasonal residence = 0)	2160	0.98	495	0.98	930	1.00	382	1.00
		(0.14)		(0.15)		(0.05)		(0.05)
Swimming pool	2194	0.41	496	0.45	930	0.47	382	0.47
		(0.49)		(0.50)		(0.50)		(0.50)
Programmable thermostats	2202	0.65	496	0.80	930	0.84	382	0.84
		(0.48)		(0.40)		(0.36)		(0.36)
Single-family house	2120	0.82	491	0.90	930	0.95	382	0.95
		(0.38)		(0.31)		(0.22)		(0.22)
Non-TOU consumers								
Ownership (renter = 0)	7824	0.72	731	0.79	537	0.81	266	0.81
		(0.45)		(0.40)		(0.39)		(0.39)
Household income ($1000)	7824	45.03	731	55.84	537	55.21	266	56.07
		(40.70)		(44.08)		(43.61)		(44.13)
Square footage (1000 ft^2)	7381	1.51	723	1.62	537	1.64	266	1.64
		(0.79)		(0.78)		(0.79)		(0.77)
Household size	7422	2.07	712	2.15	533	2.11	263	2.13
		(1.06)		(1.08)		(1.10)		(1.07)
White	7319	0.75	691	0.80	530	0.83	259	0.83
		(0.43)		(0.40)		(0.38)		(0.38)
Stories	7167	1.17	715	1.12	536	1.09	265	1.09
		(0.42)		(0.35)		(0.29)		(0.31)

Table 11 (continued)

Variable	Before matching				After matching			
	Without energy-efficient AC		With energy-efficient AC		Without energy-efficient AC		With energy-efficient AC	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Vintage	7824	29.98	731	30.00	537	30.60	266	30.32
		(19.78)		(17.21)		(18.52)		(17.18)
Primary (seasonal residence = 0)	7143	60.38	707	59.16	526	60.06	257	60.06
		(14.73)		(14.34)		(13.67)		(13.68)
Swimming pool	7510	0.90	724	0.90	537	0.92	266	0.92
		(0.30)		(0.30)		(0.26)		(0.26)
Programmable thermostats	7739	0.16	730	0.18	537	0.17	266	0.17
		(0.36)		(0.39)		(0.38)		(0.38)
Single-family house	7824	0.52	714	0.72	536	0.71	265	0.71
		(0.50)		(0.45)		(0.46)		(0.46)

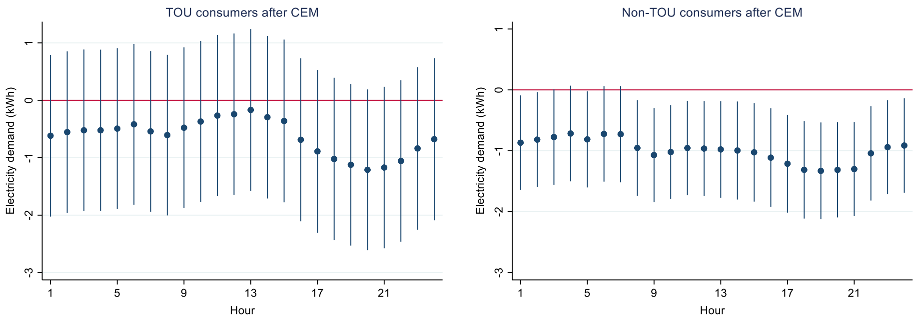

Fig. 12 Electricity savings by hour-of-day using coarsened exact matching. *Notes:* Coarsened exact matching is applied before the fixed effects regression. Each plot has 24 coefficients with 95% confidence intervals. The dependent variable for each regression is hourly electricity demand in kWh. Electricity price, CDD, HDD, holiday, and weekend are included as covariates. All regressions are estimated with household fixed effects and year, month-of-year, and hour-of-day fixed effects. The summer months are from May to October

Appendix 4: Test the Inequality of Regression Coefficients for the TOU and Non-TOU Groups

In this section, we provide a formal statistical test that TOU and non-TOU consumers have different savings, namely different sets of regression coefficients. Since they are coefficients from regressions, they cannot be examined by a simple *t* test. We set up one more regression model which nests both groups of consumers.

$$Demand_{ihd} = \alpha + \sum_{h=1}^{24} \beta_1^h EE\_AC_{id} * hour\_of\_day_h + \sum_{h=1}^{24} \beta_2^h EE\_AC_{id} * hour\_of\_day_h * TOU_i + \boldsymbol{\beta X_{ihd}} + \tau_y + \delta_m + \gamma_h + \varepsilon_{ihd}$$

Table 12 Testing of inequality for savings of TOU and non-TOU groups

Hour	Coefficient	Standard errors	t	$P > \|t\|$	[95% Conf. interval]	
Hour1	2.694	0.441	6.10	0.000	1.829	3.559
Hour2	1.941	0.355	5.47	0.000	1.246	2.637
Hour3	2.648	0.377	7.03	0.000	1.909	3.386
Hour4	2.416	0.374	6.46	0.000	1.683	3.148
Hour5	2.499	0.361	6.91	0.000	1.791	3.208
Hour6	1.999	0.373	5.36	0.000	1.268	2.730
Hour7	0.559	0.441	1.27	0.204	− 0.304	1.423
Hour8	1.581	0.416	3.80	0.000	0.767	2.396
Hour9	2.711	0.401	6.77	0.000	1.926	3.497
Hour10	2.804	0.465	6.03	0.000	1.892	3.716
Hour11	2.337	0.478	4.89	0.000	1.400	3.273
Hour12	2.956	0.532	5.55	0.000	1.912	3.999
Hour13	4.118	0.607	6.78	0.000	2.927	5.308
Hour14	4.060	0.645	6.30	0.000	2.796	5.324
Hour15	4.624	0.618	7.49	0.000	3.413	5.834
Hour16	5.918	0.663	8.93	0.000	4.619	7.216
Hour17	5.768	0.645	8.94	0.000	4.503	7.033
Hour18	5.242	0.660	7.95	0.000	3.949	6.534
Hour19	5.369	0.668	8.04	0.000	4.060	6.679
Hour20	4.003	0.577	6.93	0.000	2.871	5.134
Hour21	3.808	0.642	5.94	0.000	2.551	5.066
Hour22	3.875	0.633	6.13	0.000	2.636	5.115
Hour23	3.130	0.523	5.98	0.000	2.105	4.155
Hour24	3.115	0.478	6.51	0.000	2.178	4.053

where all the variables share the same definition as those in Eq. (1). The covariates $\boldsymbol{X}$ also include the same covariates: electricity price, CDD, HDD, holiday and weekday. We have added a new variable TOU_i to differentiate the two groups. It is equal to 1 when the consumers are TOU consumers and it is 0 otherwise. By examining the coefficients on the interaction terms $\sum_{h=1}^{24} \beta_1^h EE\_AC_{id} * hour\_of\_day_h * TOU_i$, we can test if TOU and non-TOU groups have different hour-by-day electricity savings after AC replacements. We find that the p-values ($p < 0.01$) indicate that the differences are statistically different (Table 12). We reject the null hypothesis that the difference is zero. In other words, we can conclude that the TOU group is different from the non-TOU group.

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