ABSTRACT

Title of Dissertation: ENERGY EFFICIENCY IMPROVEMENT IN BUILDINGS: ESSAYS ON THE IMPACTS, ADOPTION, AND BENEFITS

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Energy is essential for human development; however, energy consumption is also responsible for large air and greenhouse gas emissions. As the concerns about global climate change have increased, reducing energy demand has gained more importance. This dissertation focuses on energy consumption in the building sector, especially the residential building sector. Energy efficiency and conservation, as a key strategy for reducing energy demand in the building sector, is favored by advocates and policymakers because it can be a cost-effective approach to reduce energy demand. This dissertation takes a three-essay format and adds to the discussion on energy efficiency and the energy efficiency gap.

Essay 1 evaluates energy efficiency retrofits. Many past estimations of energy efficiency performance are based on the predicted savings from simulation or engineering models, and they overestimate the actual savings. This essay evaluates the

electricity savings from Energize Phoenix program in Arizona, which includes 201 residential buildings and 636 commercial buildings during 2008-2013. Fixed effects panel regression is applied, and the results show energy savings are 12% for commercial buildings and 8% for residential buildings. The realized energy savings are 30-50% lower than the predicted ones by engineering models, implying that policymakers need to rely more on the empirical evaluations. Heterogeneity also exists among retrofits for different buildings.

Essay 2 investigates the adoption of energy efficiency. Although many market and behavioral factors have been proposed to explain the low adoption level of low-carbon technologies, the impact of one particular factor-electricity rate has not been fully discussed in the existing literature. Essay 2 investigates the association between time-of-use (TOU) electricity rate and the adoption of solar panels and energy-efficient air conditioners in residential buildings. The empirical evidence suggests that TOU consumers are associated with a 27% higher likelihood of solar panel installation, but they are not more likely to adopt energy-efficient air conditioners (ACs).

Essay 3 examines the existence of the energy efficiency gap and compares the social and private benefits from energy efficiency under different rates (TOU and non-TOU rate). This essay applies data on energy efficiency retrofits and hourly electricity demand for about 16,000 households during 2013-2017. A combination of a matching approach and fixed effects panel regression is employed. The results show that the private benefits of energy efficiency exceed the social benefits under both TOU and non-TOU rates but by different degrees. These results indicate that there should be potentially different levels of policy interventions towards energy efficiency for consumers on different rates.

ENERGY EFFICIENCY IMPROVEMENT IN BUILDINGS: ESSAYS ON THE IMPACTS, ADOPTION, AND BENEFITS

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Chapter 1 Introduction

1.1 Energy efficiency in buildings

Energy is essential for supporting human development and all aspects of life; however, energy consumption is also responsible for a large volume of air and greenhouse gas emissions, which contributes to the acceleration of climate change and the increase of air pollution. As the concerns about global climate change have increased in the past few decades, reducing energy demand and changing energy supply have taken on increasingly more importance (Gillingham et al., 2016). Efforts have been made in various sectors (e.g., transportation and power sectors) to decrease the energy demand from fossil fuels and promote renewable energy. Among all sectors, this dissertation will focus on the energy consumption in the building sector, especially the residential building sector. The building sector is particularly important given that energy consumption of residential and commercial buildings contributes to up to about 30% of total carbon emissions and occupant behaviors in the buildings are accountable for 80% of the variation in energy demand (Kingma et al., 2015).

Energy efficiency and conservation is a key strategy for reducing energy demand in the building sector. Energy efficiency is favored by many advocates and policymakers because it can be a cost-effective approach to reduce energy demand (Granade et al., 2009). Billions of dollars were spent on energy efficiency products and services, among which 58% are to the building sector (EIA, 2016). Currently, the energy efficiency policies and measures implemented in the building sector include various types, such as energy efficiency retrofits, building or appliance standards, financial incentive programs, and information provision programs (Gillingham et al., 2006; Newell et al., 2014; Meyers et al., 2015; Alberini and Towe, 2015; Davis et al., 2016). Energy efficiency retrofits are among the most common one. To date, there have been a great number of energy efficiency retrofit programs in the building sector, which are supported by the governments of different levels, such as the Building America, Home Performance with Energy Star, and Weatherization Assistance programs. The scope of this dissertation is primarily limited to energy efficiency retrofits and appliance replacements, and it does not focus on building standards, incentives, and information provision. However, many of the same empirical issues carry over to them as well.

1.2 Benefits of energy efficiency

Energy efficiency has many benefits and generally increases the welfare of society. Firstly, energy efficiency helps consumers reduce electricity demand and leads to savings on bills for consumers. Energy efficiency reduces the marginal cost of energy service. For the same level of performance, improved energy efficiency means less electricity will be consumed by the appliances in the households, and thus people can save on their bills. Secondly, energy efficiency, as well as onsite renewable energy generation, reduces the carbon emissions and pollutants emitted from fossil fuels, which are still the primary energy sources nowadays. Therefore, energy efficiency can improve the air quality and thus improve the social welfare. Moreover, for electric utilities, energy efficiency also indicates fewer investments in infrastructure and avoided costs associated with electricity generation (Callaway et al., 2015; Novan and

Smith, 2018). In addition, more energy-efficient buildings are reported to have a price premium (Fuerst and McAllister, 2011). People are willing to pay more for more energy-efficient buildings and the price premium could range from 3%-7%, depending on the factors such as types of retrofits and consumers' preferences (Eichholtz et al., 2010; Brounen and Kok, 2011; Shen et al., 2020). This price premium indicates that energy efficiency can be capitalized into the value of buildings by the buyers (Brounen and Kok, 2011). Moreover, energy-efficient buildings also have positive impacts on indoor environment, occupants' productivity, labor market (Heerwagen, 2000) and corporate images, etc. (Eichholtz et al., 2010).

1.3 Energy efficiency gap

One key phenomenon associated with energy efficiency is the so-called energy efficiency gap – the failure to invest in the seemingly cost-effective energy efficiency technologies (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012). With energy efficiency gap, the private adoption level of energy efficiency is lower than the socially optimal level. Over the past few decades, extensive discussions have been provided in the literature on the energy efficiency gap (Gillingham and Palmer, 2014; Fowlie, et al., 2018). A series of market failures are found to be responsible, such as the split-incentive problem, imperfect information, and behavioral barriers.

1.3.1 The split-incentive problem

The split-incentive problem, also known as the principal-agent problem refers to the misplaced incentive between the landlords and the tenants in terms of energy efficiency adoption (Brown, 2001; Gillingham et al., 2012; Krishnamurthy and Kriström, 2015). In general, the principal-agent problem occurs when one party (agent) makes the decisions on the behalf of another (principal). As for energy efficiency, the landlords (agent) usually make the decision regarding energy efficiency investments and choose the level of energy efficiency rather than the tenants (principal) of the building. Thus, the tenants' interests are not reflected when purchasing energy-efficient appliances or retrofits. Empirical evidence shows that when the landlords decide for the tenants, there is a lower level of energy efficiency (Gillingham et al., 2012). Energy efficiency is not the priority for many landlords because they are not paying for the utilities (Davis, 2012).

1.3.2 Imperfect information

Imperfect information for the consumers also affects their level of energy efficiency adoption in the buildings. The consumers do not have enough information about the energy savings from energy efficiency technologies. Without sufficient knowledge, the consumers are less likely to adopt energy efficiency. Howarth and Andersson (1993) show that imperfect information makes consumers purchase devices that are less efficient. With more information provided such as energy audit/certificate and social comparison energy reports, there could be a further decrease in electricity use in the buildings (Ramos, et al., 2015; Alberini and Towe, 2015; Burkhardt et al., 2019; Brandon et al., 2019).

1.3.3 Behavioral barriers

Besides, behavioral barriers of consumers contribute to the energy efficiency gap (Allcott et al., 2014; Tietenberg 2009; Gillingham and Palmer, 2014). Typical behavioral failures include myopia, inattentiveness, and reference-point phenomena (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Gerarden et al., 2015).

Myopia impacts energy efficiency adoption because consumers usually have a high discount rate and give a small value to future energy savings. Consumers discount the benefits from energy efficiency which are realized in the future when they make decisions to purchase energy-efficient appliances. The discount rates are usually 20-30% and could be even higher (Hausman, 1979; Train, 1985; Wada et al., 2012; Epper, 2014).

Inattentiveness is another behavioral barrier. Consumers are inattentive to energy efficiency even if they are well-informed. The reason might be that information acquisition and calculation takes time and effort, which is costly for consumers. Consumers tend to focus more on other attributes of products (such as size and brands of fridges) other than energy efficiency, and as a result, they fail to recognize the opportunities for energy savings (Allcott and Greenstone, 2012; Fischer, 2008).

The reference-point phenomena indicate that consumers do not evaluate gains and losses equally, and instead, they evaluate the benefits and costs based on a reference point, which is usually the status quo. Consumers put more weight on an expected loss than the same amount of gain (Kahneman and Tversky 1979). Consumers are often loss averse, and they weigh the negative states more heavily although energy efficiency would have net benefits (Gillingham and Palmer, 2014).

1.3.4 Other barriers

Besides the market failures, there are other barriers also discourage energy-efficiency investments (Gillingham et al., 2009; Sutherland,1991). They could include the high initial costs, low energy prices, fluctuating energy prices, etc. Some structural/regulatory barriers, such as federal regulations on electricity prices and supply infrastructure limitations also influence the adoption of energy efficiency (Hirst and Brown, 1990).

1.4 Dissertation organization

My dissertation takes a three-essay format. All three essays add to the discussion on energy efficiency and the energy efficiency gap in the buildings.

Essay 1 evaluates energy efficiency retrofits and provides an empirical investigation of the impacts of energy efficiency retrofits. The advocates of energy efficiency often assume that the costs of retrofits pay for themselves with the energy saved. However, this calculation is usually based on the predicted savings from simulation or engineering models, and the predicted energy savings tend to overestimate the actual savings. Studies have reported that a gap of 30-40% exists between the predicted savings and actual savings. The possible reasons for the overestimation of predictions are that many factors such as behavioral factors, management practices, and organizational factors are not considered (Parker et al., 2012; Oates and Sullivan, 2012; Gillingham et al., 2012). There could also be improper installation, technology failures, and modeling or measurement inaccuracies. Therefore, evaluating the empirical savings of adopting energy-efficiency retrofits is valuable to policymakers and building owners in making energy efficiency decisions.

Essay 2 investigates the adoption of energy efficiency and explores the relationships between energy efficiency and electricity rates. Although many market and behavioral factors have been brought out in the existing literature to explain the low adoption level of low-carbon energy technologies, the impact of one particular factor-electricity rate structure is not fully discussed (Novan and Smith, 2018). Different electricity rate structures charge electricity prices in different ways and thus directly influences consumer electricity consumption behaviors as well as the resulted benefits of energy efficiency measures. Essay 2 will fill the gap in the literature by evaluating whether rate structure has an impact on the adoption of two low-carbon technologies — energy efficiency and distributed solar panels.

Essay 3 studies the overinvestment in energy efficiency under different rates. Conditional on the adoption level of energy efficiency (due to other market failures), consumers have different consumption behaviors and are charged differently under different rate plans. There is evidence that the private benefits from energy efficiency (the energy bill savings) are larger than the social benefits by 140% for consumers on increasing block rate (Novan and Smith, 2018). However, the social and private benefits of energy efficiency under other rate structures is not studied. This essay will provide such a study so that we can examine whether there is overinvestment (i.e., private savings larger than the social savings) for different rate plans.

The remainder of my dissertation proceeds as follows. Chapters 2-4 correspond to three different essays. In each essay, I will conduct a thorough literature review in the related field, describe the data, and present the empirical strategies and econometric analysis. Following that, conclusion, discussion, and policy implications are also provided.

Chapter 2 Do energy retrofits work? Evidence from commercial and residential buildings in Phoenix

2.1 Introduction

Buildings account for 40% of total energy consumption and 60% of electrical use in developed nations (Fernandez, 2007). Energy consumption contributes significantly to greenhouse gas emissions, which are the major cause of global warming. Therefore, understanding energy consumption in buildings is crucial to reducing the large volume of emissions in the United States. With high energy consumption, energy efficiency is recognized as one of the key methods to reduce energy use and mitigate climate change (Bouton et al., 2010). To date, there have been numerous energy efficiency programs supported by the federal government as well as the state and local governments.

However, discrepancies exist between realized energy savings and engineering-model predicted savings from energy efficiency (Fowlie et al., 2017; Zivin and Novan, 2016). Scheer et al. (2013) find that there is a gap of 30-40% between the energy savings predicted by engineering models and actual savings after energy retrofits. Davis et al. (2014) find that only one-quarter of predicted savings are realized for refrigerator replacements. Grimes et al. (2016) report a third of predicted energy savings after insulation treatment. Besides, Fowlie et al. (2017) show that the model-projected savings are roughly 2.5 times the actual savings for households in the Weatherization Assistance program. These studies all find that the expected energy savings based on simulation or engineering models tend to overestimate the actual savings from implementing energy efficiency programs. The possible reasons for this savings shortfall include improper installations, technology failures, and modeling or measurement inaccuracies. Moreover, the engineering models do not take into consideration all the important factors impacting energy consumption, such as behavioral factors (Parker et al., 2012), management practices (Oates and Sullivan, 2012), and organizational factors (Gillingham et al., 2012). One important factor related to behavior problems is the rebound effect (Scheer et al., 2013), in which consumers use more energy than before the retrofits because energy efficiency reduces the marginal cost of energy services, leading to fewer energy savings than would be expected (Gillingham et al., 2016). Realizing the existence of this performance gap and evaluating the empirical savings of adopting energy-efficiency retrofits is important for cost-effectiveness analysis, which is valuable to policymakers and building owners in making energy efficiency decisions.

2.2 Literature review

This essay adds to the existing literature in three respects. First, it provides an empirical assessment of energy savings after retrofits in commercial buildings. Until the time when this essay is conducted, economic studies on retrofits in residential buildings are more commonly seen (Fowlie et al., 2017; Zivin and Novan, 2016; Davis et al., 2014), while studies on energy efficiency retrofits in commercial buildings are relatively scarce. This essay differs from the existing studies on commercial energy use (Kahn et al., 2014; Qiu, 2014; Denton et al., 2003) by focusing on the effect of energy efficiency retrofits on electricity savings. Moreover, large pre-post treatment field studies that incorporate market-standard contractor work are equally rare in the existing literature and this essay will provide such an analysis.

Second, one limitation of the existing studies on residential buildings is that low-income households are more widely studied, but moderate- and high-income households are seldom included in the analysis. For example, the studies of Fowlie et al. (2017) and Zivin and Novan (2016) focus on low-income households in weatherization programs. This essay will incorporate households of different income levels and explore if there is heterogeneity among households of different income levels.

Finally, this essay investigates the effect of energy efficiency programs in an area with a very hot climate. The average summer high temperature in Phoenix is above 100 °F. Due to factors such as climate change, regions with warm climates are expanding in size and number worldwide. Global warming is inevitable, and the western United States is found to be hotter and drier (Saunders et al., 2008; McKinnon et al., 2021). Thus, the results of this essay in Phoenix can be useful for evaluating energy efficiency in other similar growing high-temperature cities.

There is an endogeneity problem for the analysis in this essay. Since the Energize Phoenix program was voluntary for consumers to participate, one concern is that some participants were more likely to participate than others, particularly more environmentally conscious consumers, larger electricity-usage consumers, and consumers more targeted by an intensive marketing campaign. These participants differ in terms of their energy consumption behaviors and therefore, this study cannot rule out the possibility of self-selection bias. Strategies such as instrument variables could address heterogeneity (Heckman et al., 2006). However, without available variables to use as a valid instrument, I use the following four strategies to address the selection bias. First, I use building-level fixed effects to control for the time-invariant building attributes. Second, I apply building×year fixed effects to control for the time-variant and building-specific factors that change from year to year. Third, I include control groups for a difference-in-difference analysis. Finally, I match treated buildings with untreated buildings using propensity score matching for a robustness check.

2.3 Program and data

2.3.1 Energize Phoenix Program

This essay evaluates an energy efficiency program called the Energize Phoenix program, led by the City of Phoenix, Arizona State University, and the state's largest electricity provider, Arizona Public Service (APS). This three-year (2010-2013) energy efficiency program targeted buildings located in the light rail corridor. It is a highly diverse, mixed-use, L-shaped region centered on the Phoenix central business district (Appendix 2A Figure 1). The intended goal of the Energize Phoenix program was to reduce energy consumption by 30% for residential buildings and 18% for commercial buildings.

The Energize Phoenix program was a market-driven program where marketing initiatives, such as community events, contractor-driven marketing and sales, and advertising in neighborhood newsletters, were used to attract people to participate. It was managed by contractors working directly with participants. The homeowners or building owners decided on which energy retrofits they wanted to adopt. The contractors provided counseling beforehand about which investments would work best for the buildings. APS and the City of Phoenix subsidized retrofits that could pass the cost-effectiveness test set by the Arizona Corporation Commission (Public Utilities Commission of Arizona). The dataset includes data for 201 residential buildings and 636 commercial buildings during the period 2008-2013.

Based on the subsidy level, the residential buildings were further divided into three groups: Energy Assist 60/40, Energy Assist 100%, and Rebate Match (Dalrymple et al., 2013). Energy Assist 60/40 was available to homeowners with an annual income of 400% of the federal poverty level or less. This group was provided a grant to cover 60% of upgrade costs. Energy Assist 100% was available to homeowners with an annual income less than 200% of the federal poverty level. Households in this program were reimbursed for 100% of upgrade costs. Consumers in the Rebate Match group also participated in the Home Performance with Energy Star program and got matched rebates from the utility's programs. They were typically higher-income homeowners.

Residential buildings received a combination of the following five retrofit measures, including upgrades in air conditioner, insulation, duct sealing, air sealing, and shade screens. There were six retrofit measures for commercial buildings, including upgrades in HVAC (heating ventilation, and air conditioning), light bulbs and fixtures, refrigeration, pumps or motors, lighting controls, and windows. The ratios of buildings that receive different retrofits are listed in Table 2A-1. A building may have received only one retrofit or a combination of retrofits (referred to hereafter as a "retrofit bundle"). The most popular retrofit bundle for residential buildings was the combination of insulation, duct sealing, and air sealing. The most popular retrofit bundle for commercial buildings was a lighting retrofit by itself.

2.3.2 Data and summary statistics

The collection of electricity billing data started before the Energize Phoenix program and spanned January 2008 through April 2013[1]. The panel data is unbalanced because slightly fewer data are available at the beginning and towards the end of the study period. Data on building attributes were also collected during the audit of the buildings. It is possible that some buildings registered for the program but dropped out later and did not have the retrofits implemented.

The dataset in this essay includes (1) building-level monthly electricity billing data from APS; (2) retrofit information, including the retrofit date, the final cost and the estimated savings for each building; and (3) physical attributes of buildings and social-demographics of households (data on residential building attributes were collected by APS while data on social demographics of residential buildings and commercial building attributes were collected through surveys) (James et al., 2013), records of cooling degree days (CDD), heating degree days (HDD), and electricity rates from APS.

[1] The period of the analysis is from January 2008 to April 2013. Not every building has data for the whole study period and thus the dataset is not balanced. The control period for each building is different because the installation date of treatment varies by building. The installation dates of treatment range from Feb 2011 to June 2013. The pre-treatment period serves as the control period for each building.

There are 201 residential buildings that have received retrofits. Among all residential buildings, 72% of the buildings received retrofits in 2012 and the rest received the retrofits in other years. There is a total of 10,235 observations for residential buildings. There are 636 commercial buildings that have received retrofits. Among them, 57% of buildings received retrofits in 2012. There is a total of 35,681 observations for commercial buildings. The descriptive statistics of the key variables are shown in Table 2-1. Multi-family residential buildings are not included because of their small sample size. Figure 2-1 shows the summary statistics of electricity use before and after retrofits without conducting an econometric analysis. There is a visually observable trend that electricity consumption for both residential and commercial buildings decreased after energy efficiency retrofits.

Table 2-0 Descriptive statistics for key variables

Variable	Mean	Std. Dev.	Min	Max
Residential buildings (N=10,235)				
Energy use (kWh)	1157	845	2	7610
Air conditioner	0.012	0.110	0	1
Insulation	0.145	0.352	0	1
Duct sealing	0.170	0.375	0	1
Air sealing	0.168	0.374	0	1
Shade screens	0.043	0.204	0	1
CDD	11.081	11.767	0	34.08
HDD	0.497	2.293	0	16.08
Commercial buildings (N=35,681)				
Energy use (kWh)	110313	406337	2	6997714
HVAC	0.007	0.081	0	1
Lighting	0.158	0.365	0	1
Refrigeration	0.004	0.066	0	1
Pumps/motors	0.011	0.103	0	1
Controls	0.020	0.142	0	1
Windows	0.005	0.068	0	1
CDD	22.904	15.310	0	49.08
HDD	0.474	2.255	0	16.08

Cumulative density functions for energy savings (calculated as the difference between post- and pre-treatment energy consumption) by residential buildings and commercial buildings (Appendix 2A Figure A2) indicate that there is a large variance associated with the savings. For all buildings, the probability that electricity savings achieving the estimated average savings or beyond is a little over one-third.

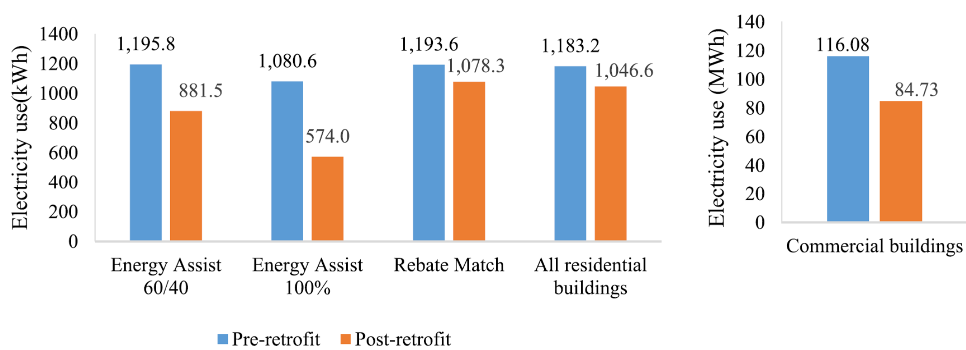

Figure 2-1 Summary statistics of monthly pre-treatment and post-treatment electricity use.
Note: Participants in Energy Assist 60/40 are typically middle-income households, those in Energy Assist 100% are low-income households, and those in Rebate Match are high-income households.

In some cases, building owners registered for the program but opted out before retrofits were installed. These buildings can potentially serve as control buildings and their electricity consumption data was also available to the program. There are 17 such residential buildings and 48 such commercial buildings. Electricity use data for other buildings not participating in the program in the light rail area are not available to us. The descriptive statistics of building attributes show that the average square footage of control buildings and treated buildings are not comparable (Table 2A-2). There is a discussion of analysis with control buildings included in section 2.4.6 for robustness checks, but the main results are based on the results without control buildings.

2.3.3 Methods

Due to the endogeneity, there are several potential sources of bias in the estimation of treatment effects. First, it is likely that the buildings with larger pre-treatment energy consumption (more likely less-energy-efficient buildings to start with) are more motivated to participate because their owners want to reduce their energy bills more. These types of buildings have a larger potential for energy reduction than the average building, which could lead to an overestimation of the treatment effects. Second, studies (e.g., Bamberg, 2003) show that environmentally concerned participants are more likely to participate in energy efficiency programs than others. These participants might pay more attention to energy use post-treatment, which would lead to an overestimation of energy savings. On the other hand, it is also possible that these environmentally concerned people have already adopted some energy efficiency measures prior to the Energize Phoenix program, which would lead to less potential for energy savings under this condition and thus there will be an underestimation of the savings.

To address the selection bias and to investigate the causal effects of retrofits on energy consumption, the fixed effects method is employed by regressing electricity consumption on energy efficiency retrofits and other covariates. The dependent variable is the natural log of monthly electricity use and the independent variables include electricity price, retrofit treatment, CDD, HDD, building attributes, etc. The model uses the average electricity price given that there is evidence that consumers respond to the average price rather than the marginal price (Ito, 2014). The electricity prices are based on the standard rates (increasing block rates) from APS, without considering other pricing plans. CDD and HDD are included in the model to control for the impact of temperatures on electricity consumption. CDD refers to how many degrees are above 65 °F. HDD refers to how many degrees are below 65 °F.

To estimate the overall treatment effects, I use a dummy variable indicating the treatment status of energy efficiency retrofits:

$$In(Electricity_{it}) = \alpha T_{it} + \beta P_{it} + \delta_1 CDD_t + \delta_2 HDD_t + \eta_i + \xi_t + \varepsilon_{it} \quad \text{(2-1)}$$

where *Electricity* is the monthly electricity use (kWh); *i* indicates an individual building; *t* indicates the different months in different years; T_{it} equals one if the building has received treatment at time *t* and zero otherwise; P_{it} is the electricity price; δ_1 and δ_2 are coefficients for *CDD* and *HDD*, which control for temperature variation on electricity use; η_i is individual building fixed effects controlling for any unobservable attributes of buildings that do not change over time, such as building structural attributes and neighborhood infrastructure development; ξ_t is monthly fixed effects controlling for factors that influence all buildings at the same time, such as policy changes.

To disentangle the effect of each type of retrofit, the model specification is revised as:

$$In(Electricity_{it}) = \boldsymbol{\alpha}'\boldsymbol{T}_{it} + \beta P_{it} + \delta_1 CDD_t + \delta_2 HDD_t + \eta_i + \xi_t + \varepsilon_{it} \quad (2\text{-}2)$$

where $\boldsymbol{T_{it}}$ is the vector of treatment dummy variables including five types of retrofits for residential buildings, and six types of retrofits for commercial buildings. The meanings of other variables are the same as in equation (2-1). This model specification is also applied to study the effects of retrofit bundles by replacing $\boldsymbol{T_{it}}$ of individual retrofits with retrofit bundles.

To control for time-variant individual factors for each building, such as changes in financial status and environmental awareness of occupants, which influence energy consumption and treatment status, building×year fixed effects η_{iy} are used. The building×year fixed effects model for energy use is described by equation (2-3):

$$In(Electricity_{it}) = \boldsymbol{\alpha}'\boldsymbol{T}_{it} + \beta P_{it} + \delta_1 CDD_t + \delta_2 HDD_t + \eta_{iy} + \xi_t + \varepsilon_{it} \quad (2\text{-}3)$$

To examine the learning effects of participants for energy savings, I introduce L_{it}, which is the number of months after the retrofits, and it is zero before the treatment. ${L_{it}}^2$ it is the square term of L_{it}. I add the interaction terms $T_{it}L_{\ it}$ and ${L_{it}}^2$ into equation (2-1).

$$In(Electricity_{it}) = \alpha T_{it} + \beta P_{it} + \gamma_1 T_{it}L_{\ it} + \gamma_1 T_{it}{L_{\ it}}^2 + \delta_1 CDD_t + \delta_2 HDD_t + \eta_i + \xi_t + \varepsilon_{it} \quad (2\text{-}4)$$

I drop the month of retrofits because that month is mixed with pre- and post- treatment periods. A one-month replacement time is also assumed in Davis et al. (2014). I also include an alternative 2-month retrofit period for robustness check in Appendix 2C. Moreover, the vacancy of the building could influence its energy use significantly since an empty house would consume significantly less electricity. I incorporate a dummy variable to indicate vacancy, for which the electricity use of the building is within the lowest 1%. In the regression, I drop the observation if the buildings are vacant. I also conduct other robustness checks using alternative vacancy thresholds of 2% and 5% in Appendix 2C.

If there are other contemporaneous large retrofits besides the Energize Phoenix programs in a large fraction of the buildings during the study period, there will be an overestimation of savings because the statistical significance would also be a result of these non-program retrofits. However, such concern is less of an issue for this study. Since large retrofits are normally very expensive, other large retrofits are less likely in low-income and middle-income families. If high-income households adopt these other large retrofits, they will ask for rebates from Arizona Public Service, and thus they will be eligible for the program and will be recorded and included in the data. Therefore, I feel comfortable asserting that no other large retrofits took place beyond those in the Energize Phoenix program. Additionally, solar water heaters were among the available retrofits in the Energize Phoenix program, and there were about 50 solar water heater installations. However, these observations are excluded from the study because some water heaters could use natural gas and natural gas consumption data, which is unavailable to us[2]. I also do not have data on solar panel installation. If the solar panel

[2] Because the main purpose of the Energize Phoenix program is to save electricity, data on electricity use are carefully collected for this program. I do not have total energy consumption data, and therefore

installations are correlated with energy efficiency retrofits in the program, then I may overestimate the electricity savings of the program.

2.4 Results

2.4.1 Overall effects of retrofits

Table 2-2 shows the results based on the estimation of equation (2-1). The results indicate that for residential buildings the retrofits reduce monthly electricity use by 8% ($p< 0.01$). It might be possible that some unobserved, individual-level, and time-variant factors (such as personal preferences for desirable temperatures) influence both the selection of energy retrofits and total energy use, which can lead to biased estimations. Therefore, I also use building×year fixed effects, which can control for individual-level factors varying from year to year. I find the coefficients are very similar for residential buildings with and without building×year fixed effects.

For commercial buildings, the monthly electricity savings are approximately 12% ($p<0.01$), and energy savings upon controlling for building×year fixed effects become smaller. This indicates that treatment effects vary for the same buildings from year to

the estimation of electricity savings might include some substitution effect between electricity and other types of energy such as natural gas. However, such substitution effects might be small. Although natural gas is also used in Phoenix, I would assume that switching to natural gas is not very common because (1) the cost of changing building infrastructure in order to make a fuel switch for water heaters or space heaters is high, which is likely to be a deterrent to consumers; (2) the energy demand for space heating in Phoenix is very limited due to the mild winter, which makes it less attractive to switch to natural gas as a cost-saving measure. Usually, natural gas used for water heating is more common. The Energize Phoenix program had retrofits of water heaters; however, they are not included in this essay because the fuels for water heaters are very diverse (e.g., electricity, natural gas, and solar).

year and that the impacts from time-varying factors such as the number of occupants could change from year to year[3]

[3] It is possible that new tenants can come in after the retrofits and could impact the treatment effects due to changes in building occupancy. However, usually, new tenants will have new utility account numbers and it is not likely the consumption of old tenants and new tenants will be recorded together in the dataset. The data in the study is at the utility account level instead of at the building level. When new tenants move in, the dataset will stop recording the energy consumption of that building. However, for commercial buildings, when there is no change in utility account number, there could still be a change

Table 2-2 Energy savings of retrofits on residential buildings and commercial buildings

	Residential buildings								Commercial buildings	
	Energy Assist 60/40		Energy Assist 100%		Rebate Match		Total		Total	
Electricity price	9.429	0.166	13.769***	12.031**	15.303***	10.022***	14.240***	9.003***	2.212	4.523***
	(6.903)	(5.271)	(3.979)	(4.039)	(2.057)	(1.924)	(1.783)	(1.619)	(1.745)	(1.330)
Retrofit	-0.302***	-0.365***	-0.041	0.121	-0.069**	-0.068**	-0.082***	-0.079***	-0.125***	-0.057***
	(0.103)	(0.123)	(0.116)	(0.173)	(0.031)	(0.033)	(0.026)	(0.030)	(0.030)	(0.018)
CDD	0.005	0.040***	-0.084**	0.019***	-0.058***	0.021***	-0.058***	0.023***	-0.032***	0.013***
	(0.016)	(0.008)	(0.029)	(0.006)	(0.012)	(0.003)	(0.011)	(0.003)	(0.003)	(0.000)
HDD	0.020***	0.011***	-0.020	0.013	-0.012	0.015***	-0.013	0.014***	-0.081***	0.002**
	(0.007)	(0.003)	(0.032)	(0.008)	(0.008)	(0.002)	(0.008)	(0.002)	(0.008)	(0.001)
Building fixed effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Month-of-sample fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Building× year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

No. of observations	1234	1234	799	799	7906	7906	9939	9939	34736	34736
R^2	0.720	0.797	0.748	0.773	0.722	0.769	0.719	0.767	0.348	0.465

Note:
The dependent variable is the natural log of monthly electricity consumption in kWh. The standard error (in parentheses) is clustered at the building level. * Significant at 10% level, ** Significant at 5% level and *** indicates Significant at 1% level.

The treatment effects are heterogeneous among households of different income levels. The retrofits reduce monthly electricity use by 26% (0.302 log point, $p<0.05$[4]) for Energy Assist 60/40 (middle-income families) and 7% ($p<0.10$) for Rebate Match (high-income families), but electricity savings are not found for Energy Assist 100% ($p>0.10$), which includes mainly low-income households. One possible reason for the lack of electricity savings is the rebound effect. The low-income households live in comparatively older houses since these houses are cheaper due to filtering and sorting (Brueckner and Rosenthal, 2009). Although location also influences the property sale prices (Glaeser and Gyourko, 2005), filtering is the dominant reason for cheaper and older houses since the study area is around the downtown central business district. The older houses are in worse condition and the occupants are also farther away from their satiation point in terms of living comfort, and thus there are larger rebound effects for these households after energy efficiency retrofits.

2.4.2 Individual retrofit effects

I separate electricity savings achieved by each retrofit measure using equation (2-2). The treatment effects of individual retrofits, as shown in Figure 2-2, are heterogeneous among households with different income levels. The insulation retrofit reduces the electricity consumption by approximately 39% (0.491 log points, $p<0.05$) for Energy Assist 60/40, the air conditioner retrofit decreases electricity use by 24% (0.272 log

[4] For log-linear regression such as $In(y) = \beta_0 + \beta_1 x + \epsilon$, the percentage change in y given one unit change in x should be calculated using %Δy= 100($e^{\beta_1} - 1$). For example, in this case, based on Table 2, the coefficient for Retrofit is -0.302 for the Energy Assist 60/40 program, which means 0. 302 log point change in energy consumption. Then the percentage change in energy consumption after retrofit is calculated using 100($e^{-0.302} - 1$), which means 26% drop in energy consumption.

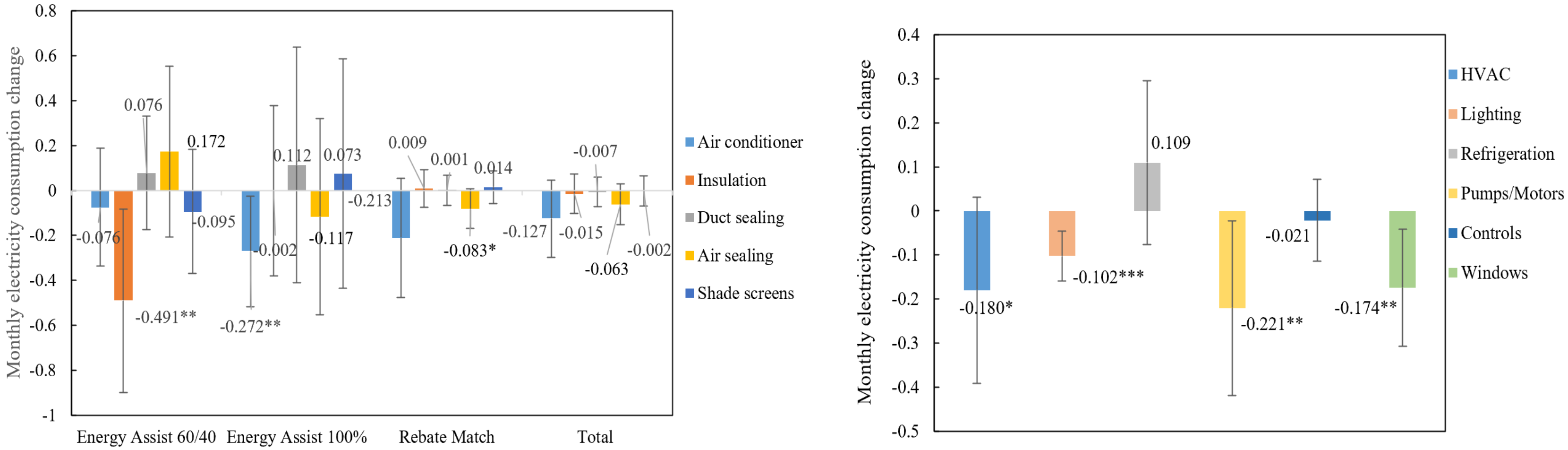

Figure 2-2 Effects of different types of retrofit on electricity use for residential buildings.
Note:
The results are from estimating equation (2-2). The dependent variable is the natural log of monthly electricity use in kWh. The model includes building fixed effects and month-of-sample fixed effects. The error bars show the 95% confidence interval. The monthly electricity use change is log point. The number of observations is 10,040 for all residential buildings.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level

points, $p<0.05$) for Energy Assist 100%, and the air sealing retrofit leads to electricity savings of 8% (0.083 log points, $p<0.10$) for households in Rebate Match. This indicates that if the main objective is electricity-usage reduction, air conditioner upgrades are the most appropriate to provide for low-income families, insulation retrofits are more suitable for middle-income families, and air sealing retrofits are more appropriate for high-income families.

Several types of retrofits have statistically significant impacts on reducing electricity use for commercial buildings (Figure 2-2). Retrofits of pumps/motors are the most effective, followed by HVAC, windows, and then lighting retrofits. The comparatively simple retrofits such as upgrades in windows and lighting are also those that save relatively less energy, in contrast to the more complicated upgrades of pumps/motors and HVAC. The treatment effects of individual retrofits using building×year fixed effects are shown in Table 2A-3.

2.4.3 Retrofit bundle effects

I examine the seven most popular bundles for residential and commercial buildings (Figure 2A-3). The retrofit bundles for different groups of residential buildings have significant effects on electricity savings, ranging from 22% (0.243 log points, $p<0.05$) to 58% (0.869 log points, $p<0.01$). The retrofit bundle7, which is a combination of air conditioner, insulation, duct sealing, and air sealing, is the most efficient retrofit bundle for all residential buildings. Interestingly, bundle7 is also the least adopted among all the seven popular bundles by buildings, probably because of its high cost and complexity. Similar to the individual retrofit effect, there is heterogeneity in bundle effects among different residential buildings. For commercial buildings, four out of the seven bundles have significant impacts. The retrofit bundle of HVAC and pumps reduces electricity use by 73% (1.312 log points, $p<0.10$).

This essay also explores how building attributes such as square footage, number of occupants, and house insulation condition interact with retrofits on treatment effects (see Appendix 2B). The results demonstrate that building attributes have an impact on treatment effects.

2.4.4 Impacts by season

I investigate whether the impacts of retrofits are influenced by the season of retrofit implementation and energy savings during the winter season (November to April) and summer season (May to October) are estimated separately. Table 2-3 shows that the interaction of *retrofit* and *summer* is statistically significant and positive for Energy Assistant 100% program. This indicates that low-income households save more electricity during the winter than in the summer. For commercial buildings, the interaction term is statistically significant and negative, implying that commercial buildings save more during the summer season.

I also add interaction terms of individual retrofits and summer season to further investigate different impacts between seasons (Table 2-4). The results show that the low-income households that adopted air conditioner retrofits save less energy during the summer season, which could be partially explained by the rebound effect for low-income families. Aydin et al. (2017) show that the rebound effect is strongest among lower-income groups because these households are farther away from their satiation point of using energy services. Low-income homes may have been kept at uncomfortable temperatures prior to the installation of energy retrofits, and they are more likely to make their houses more comfortable after retrofits. The study provides indirect evidence that there is a potential for larger rebound effects for low-income households during the summer. However, the settings of the air conditioner thermostats in those households are not available to us to further verify this hypothesis.

2.4.5 Learning effects

Based on equation (2-4), I explore the learning effects of energy savings after the adoption of retrofits. The results provide evidence for learning-by-using, as indicated by the negative coefficients of the interaction terms of *Treatment* and *Post-treatment Months* (Table 2-3). For commercial buildings, the coefficient of the interaction term of *Treatment* and the square of *Post-treatment Months* is positive. This indicates that as post-retrofit months increase, energy savings increase but at a decreasing rate before reaching a maximum point. After that, energy consumption begins to increase, and energy savings begin to decrease. The maximum points of energy savings are reached approximately one year after the retrofits for commercial buildings. Overall, there is improved learning and control of energy use after the retrofits and there exists a maximum point for energy savings. However, the learning effects are affected by the adoption and diffusion patterns of consumers (Mulder et al., 2003), and thus the observed learning-by-using in this essay could be unique for its participants in this program.

Table 2-3 Overall treatment effects by season and by the number of post-treatment months

	Residential buildings								Commercial buildings	
	Energy 60/40	Assist	Energy Assist 100%		Rebate Match		Total		Total	
Electricity price	9.430 (6.906)	9.442 (6.808)	13.769*** (3.979)	13.758*** (4.020)	15.308*** (2.057)	15.238*** (2.075)	14.244*** (1.782)	14.181*** (1.794)	2.247 (1.748)	2.220 (1.738)
Retrofit	-0.308** (0.118)	-0.165 (0.103)	-0.553** (0.241)	0.098 (0.277)	-0.092** (0.042)	-0.083** (0.037)	-0.117*** (0.036)	-0.079** (0.033)	- 0.098*** (0.030)	-0.076** (0.030)
Summer[a]	-0.107 (0.587)		0.409 (0.353)		0.726*** (0.132)		0.668*** (0.122)		0.411*** (0.045)	
Retrofit×summer	0.078 (0.248)		0.513** (0.207)		0.046 (0.054)		0.072 (0.049)		-0.053** (0.024)	
Retrofit×post-treatment months		- 0.079* (0.040)		-0.151 (0.184)		0.008 (0.010)		0.002 (0.010)		-0.013*** (0.005)
Retrofit×post-treatment months^2		0.005 (0.003)		0.031 (0.026)		-0.001 (0.001)		-0.001 (0.001)		0.0005** (0.0002)
CDD	0.005 (0.016)	0.005 (0.020)	0.018 (0.016)	-0.084** (0.037)	0.027*** (0.005)	-0.065*** (0.011)	0.023*** (0.005)	-0.064*** (0.011)	0.009*** (0.002)	-0.031*** (0.003)
HDD	0.020*** (0.007)	0.017* (0.009)	0.043** (0.015)	-0.017 (0.041)	0.041*** (0.004)	-0.020** (0.009)	0.038*** (0.003)	-0.020** (0.008)	0.019*** (0.005)	-0.081*** (0.008)
No. of observations	1234	1234	799	799	7906	7906	9939	9939	34736	34736
R^2	0.720	0.722	0.748	0.749	0.722	0.724	0.719	0.720	0.349	0.349

Note:

The dependent variable is the natural log of monthly electricity use in kWh. All columns include building fixed effects and month-of-sample fixed effects. The standard error (in parentheses) is clustered at the building level.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.
[a] The winter season is from November to April and the summer season is from May to October.

Table 2-4 Treatment effects of individual retrofits on electricity use by season

	Residential buildings				Commercial buildings	
	Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total	Total	
Electricity price	10.094	13.400***	15.263***	14.246***	Electricity price	2.282
	(6.752)	(4.127)	(2.078)	(1.784)		(1.740)
Air conditioner	0.091	-0.925***	-0.274***	-0.209**	HVAC	-0.217**
	(0.126)	(0.232)	(0.096)	(0.082)		(0.090)
Insulation	-0.511***	-0.013	0.036	0.024	Lighting	-0.080***
	(0.159)	(0.183)	(0.059)	(0.056)		(0.029)
Duct sealing	0.111	0.246	-0.068	-0.062	Refrigeration	0.070
	(0.127)	(0.200)	(0.049)	(0.047)		(0.096)
Air sealing	0.027	-0.065	-0.025	-0.056	Pumps/motors	-0.163***
	(0.120)	(0.193)	(0.064)	(0.057)		(0.062)
Shade screens	0.222	0.520***	-0.022	0.014	Controls	-0.022
	(0.144)	(0.162)	(0.055)	(0.050)		(0.041)
Summer[a]	-0.042	0.588*	0.734***	0.673***	Windows	-0.068
	(0.536)	(0.311)	(0.128)	(0.120)		(0.107)
Air conditioner×summer	-0.227	0.653***	0.096	0.107	Summer	0.403***
	(0.161)	(0.210)	(0.107)	(0.076)		(0.044)
Insulation× summer	-0.010	N/A[b]	-0.045	-0.062	Air conditioner× summer	0.045
	(0.291)		(0.070)	(0.067)		(0.121)
Duct sealing× summer	-0.006	N/A[b]	0.112	0.090	Lighting×summer	-0.043*
	(0.174)		(0.075)	(0.068)		(0.023)
Air sealing× summer	0.236	N/A[b]	-0.096	-0.006	Refrigeration× summer	0.076
	(0.242)		(0.087)	(0.075)		(0.084)
Shade screens× summer	-0.527***	-0.621**	0.052	-0.025	Pumps/motors× summer	-0.106
	(0.141)	(0.234)	(0.070)	(0.066)		(0.109)
					Controls× summer	-0.002
						(0.048)
					Windows× summer	-0.153
						(0.100)
CDD	0.005	0.024	0.027***	0.024***	CDD	0.009***
	(0.016)	(0.015)	(0.005)	(0.005)		(0.002)
HDD	0.021***	0.036**	0.040***	0.037***	HDD	0.020***

	(0.007)	(0.016)	(0.004)	(0.003)		(0.005)
No. of observations	1234	799	7906	9939		34736
R^2	0.731	0.750	0.724	0.720		0.350

Note:
The dependent variable is the natural log of monthly electricity use in kWh. All columns include building fixed effects and month-of-sample fixed effects. The standard error (in parentheses) is clustered at the building level.
* Significant at 10% level.** Significant at 5% level. *** Significant at 1% level.
[a] Winter season is from November to April and summer season is from May to October.
[b] Variable dropped due to multicollinearity.

2.4.6 Contractor impact on treatment effects

The contractors responsible for the implementation of the retrofits have an impact on the treatment effects and there can be varying energy savings. There are 27 contractors for residential buildings and 61 contractors for commercial buildings. I include the impact of the contractors by adding interaction terms of *Treatment* and dummy variables indicating different contractors. The changes in energy use vary from -36% to 43% for different contractors of residential buildings while varying more significantly for commercial buildings (Appendix 2A Figure A4). The heterogeneous savings might point to the possibility of varying contractor quality or the possibility that different contractors implement different types of retrofits. From the dataset, I can identify the companies that are better at saving energy than others. However, most contractors only worked on a small number of buildings, which makes the number of observations insufficient for persuasive statistical analysis. Given that contractors in this program often specialize in certain types of retrofits, it is very likely that the heterogeneity in contractor effect reflects the difference in retrofits.

2.4.7 Analysis with control buildings

The dataset also contains buildings that did not receive any energy retrofits, in which the owners registered to participate in the program but opted out before installation. There are 48 potential control residential buildings and 17 control commercial buildings.

I first conducted a robustness check with all these non-treated buildings included as control buildings and results show that energy savings are slightly smaller for all residential buildings, commercial buildings, and Energy Assist 60/40 (Table 2A-4). However, these control buildings are not exactly comparable to the treatment buildings in terms of the key building attributes, and thus they are not good counterfactuals for the treated buildings.

I then conducted another robustness check using the propensity score matching method to refine the control group. I matched treated buildings with control buildings that either dropped out of the program or got retrofits after May 2015 (by which the data collection had ended). Propensity score matching is applied using a probit model on the binary treatment variable. Treated buildings are matched with the untreated buildings with the most similar attributes. I use building type (office building or not), pre-treatment summer average electricity use, pre-treatment average winter electricity use, and square footage as matching attributes for commercial buildings and use building type (low-income households or not), pre-treatment average summer electricity, and average winter electricity use to find matches for the residential buildings. The building attributes before and after matching are shown in Table 2A-5 and the fixed effects model results using the matched control buildings are shown in Table 2A-6. The propensity score matching still shows 8% savings for commercial buildings and 4% for residential buildings. However, since I had a limited quantity of non-treated buildings to choose as control buildings, the matching results are not optimal. Therefore, I still base the main discussion on the results without using matching.

2.4.8 Cost-effective analysis

The cost-effectiveness of the Energize Phoenix program is evaluated based on the estimates of energy savings. Costs of retrofits refer to the total payments by all parties, including the participants, APS, and the City of Phoenix. Annual dollar savings are assessed using the average energy prices of 9.35 cents per kilowatt-hour for the commercial buildings, and 10.73 cents per kilowatt-hour for the residential buildings (Dalrymple et al., 2013). The costs only include the costs of retrofits and do not include the administration, commodities, and training costs. Annual dollar savings are calculated by multiplying energy savings by electricity prices. A payback period (when assuming zero interest rate) is estimated to be 2.7 years for the commercial buildings, whereas a payback period is estimated to be 30.4 years for the residential buildings (Table 2-5). When assuming a 5% discount rate, the payback period for commercial buildings becomes 2.9 years, and residential buildings will never pay back considering the lifespan of retrofits (Dalrymple, et al., 2013).

Based on the cost of retrofits and estimated savings, the cost per kilowatt-hour saved is $0.018 for commercial buildings throughout the lifespan of retrofits and $0.434 for residential buildings. At a 5% discount rate, the estimated savings for residential buildings are 19-32% of the upfront cost, which indicates that the savings from retrofits of residential buildings are small compared to the upfront costs.

I also report the annual internal rate of return- the discount rate at which the present value of money saved after retrofits equates to the upfront cost. The internal rate of return for commercial buildings is higher at 36.8% while the internal rate of return for residential buildings is lower and negative. This essay is consistent with the findings from another study, which also shows that energy efficiency programs can be very costly for residential buildings (Joskow and Marron, 1992). There is uncertainty concerning the cost-effectiveness analysis since it could be greatly impacted by the measurement of all the relevant costs and the lifespan of the retrofits (Joskow and Marron, 1992).

The payback periods differ for commercial and residential buildings, which might be related to different turnover/ownership times. It is possible that when commercial consumers make decisions to invest in energy efficiency, they prefer retrofits with a shorter payback period. The long payback period found for residential buildings is consistent with the existing literature, which indicates a period over 10 years (Leinartas and Stephens, 2015; Rodrigues, et al., 2015).

Table 2-5 Cost-effectiveness of Energize Phoenix program

	Commercial buildings	Residential buildings			
		Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total
No. of buildings	636	24	14	163	201

Payments($)	26,530,134	173,324	109,022	461,672	744,019
Annual energy savings (kWh)	1.063E+08	89545	-	163427	228323
Annual dollar savings	9940121.70	9608.19	-	17535.79	24499.08
Payback period (year)	2.7	18.0	-	26.3	30.4
Internal rate of return	36.83%	-19.28%	-	-25.20%	-27.26%

Note:

[a] The Energy Assist 100% program does not have energy savings according to the estimation.

[b] The upfront cost includes only the retrofit implementation cost; other related costs are not included.

2.5 Discussion

This essay empirically estimates the energy savings from adopting retrofits in commercial and residential buildings in Phoenix, Arizona. The overall energy savings after energy retrofits are 12% for commercial buildings and 8% for residential buildings. The quality of the buildings could determine the greenhouse gas emissions (GHG) emissions because buildings contribute significantly to GHG emissions. In recent years, concerns about global warming and high energy demand have led to increasing efforts to improve building efficiency. If 0.42 kg carbon emission per kWh is assumed (Fowlie et al., 2018), the avoided emissions of the Energize Phoenix program are estimated as 4.5×10^4 t annually based on the estimated electricity savings.

Energy savings are evident for middle-income and high-income households. However, there are no energy savings for low-income families. One possibility for the absence of energy-saving for low-income households is the rebound effect, which indicates the behavioral change of occupants is large so that the possible energy savings are offset. The rebound effect is more obvious with the low-income households because these occupants are more likely to be far away from the satiation point with more potential for behavioral changes. I do not find empirical evidence of the rebound effect in the commercial sector probably because the pre-retrofit comfort level is more satisfactory in commercial buildings, leaving little room for the rebound effect (Qiu, 2014). It is also possible that the occupants in commercial buildings lack control over energy technologies such as temperature settings, thus obfuscating the rebound effect.

The lighting retrofits are mostly supported in the Energize Phoenix program because they are easy to implement and have lower costs relative to the expected energy savings. The results indicate that such a subsidization decision is sensible ex-post as the lighting retrofits are statistically significant in reducing energy use by 10%. For residential buildings, the retrofits with the most significant impact are insulation retrofits that lead to a reduction of 39% for the Energy Assist 60/40 program. The fact that insulation upgrade works well is supported by Adan and Fuerst (2016), which reports that the single most effective energy-saving measure in households is insulation, reducing total annual energy consumption by 8%.

The predicted energy savings are estimated by the contractors through standard software modeling. After comparing the predicted savings with the empirical savings, this essay finds that there is an overestimation by engineering modeling (Table 2-6), which is consistent with the findings in previous literature. The achieved energy savings deviate noticeably on the downside: by 28.3% for residential and 48.5% for commercial buildings. The gap between the predicted and achieved savings is most prominent for the low-income households in the Energy Assist 100% program. Over-prediction by the contractors for commercial buildings is also observed in the report of (Reddy et al., 2014). Furthermore, the achieved energy savings of the Energize Phoenix program fall short of the targeted savings from the program design, which are 30% for residential buildings and 18% for commercial buildings. Although this essay finds that the gap between model prediction and empirical savings is comparatively large, after proper model validation and calibration, model accuracy could be improved and model prediction could be similar to actual savings (Ruiz and Bandera, 2017; Yang et al., 2019).

Table 2-6 The comparison between the predicted and empirical energy savings

	Residential buildings				Commercial buildings
	Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total	
Prediction savings percentage	30.5%	67.2%	34.0%	36.2%	60.3%
Empirical savings percentage	26.1%	0%	6.7%	7.9%	11.8%
Gap between predicted and empirical estimation	4.4%	67.2%	27.3%	28.3%	48.5%
No. of buildings	23	14	140	177	631

Note:

[a] The predicted savings after retrofits are the estimates reported by the contractors in the Energize Phoenix program.

[b] The empirical savings are from the results estimated in this study.

[c] The number of buildings is slightly less than that in the main regression analysis because of missing data on the predicted savings.

Literature provides sufficient evidence that there is a price premium for green buildings and energy efficiency can be capitalized into sale prices (Walls et al., 2017; Fuerst and McAllister, 2011). The premium is reported to be about 3% (Brounen and Kok, 2011; Eichholtz et al., 2010, 2013). This premium indicates that private consumers take energy efficiency into consideration (Brounen and Kok, 2011), and tenants and investors also capitalize on energy savings in their investment decisions. It is very likely that the real estate market in Phoenix would also capitalize on energy efficiency. However, no study has specifically analyzed the price premium of green buildings in Phoenix. Without transaction data in this study, the capitalization of energy efficiency could be a future subject of study.

Given these findings, I make the following policy recommendations: First, measures should be taken to ensure the quality of retrofits, such as setting up energy retrofits standards to minimize technology instability as well as performing additional quality assurance to improve savings estimations and maximize effectiveness. Energy efficiency programs should also make sure that qualified contractors are recruited. According to the experts of the Energize Phoenix program, the quality of some installations was not well controlled, which led to a gap between predicted savings and actual savings. Policymakers should also increase the availability of more effective retrofits that have a significant influence on the achieved savings (Shonder, 2014). Second, policymakers should incorporate occupants' behaviors into the decision-making process (Van den Bergh, 2011). There is a potential that consumers can be motivated to change their behaviors to save more energy. Multiple instruments such as providing information, increasing consumer awareness, and behavioral psychology techniques (e.g., marketing by contractors) can be applied to encourage behavioral changes. Third, most energy efficiency programs are supported or partially supported by electric utilities, whose primary revenues depend on electricity sales. Since energy efficiency programs may reduce the revenues for electric utilities under traditional rate-making policies, de-coupling policies could be implemented to ensure that utilities are rewarded for promoting energy efficiency.

2.6 Appendices

Appendix 2A: Figures and Tables

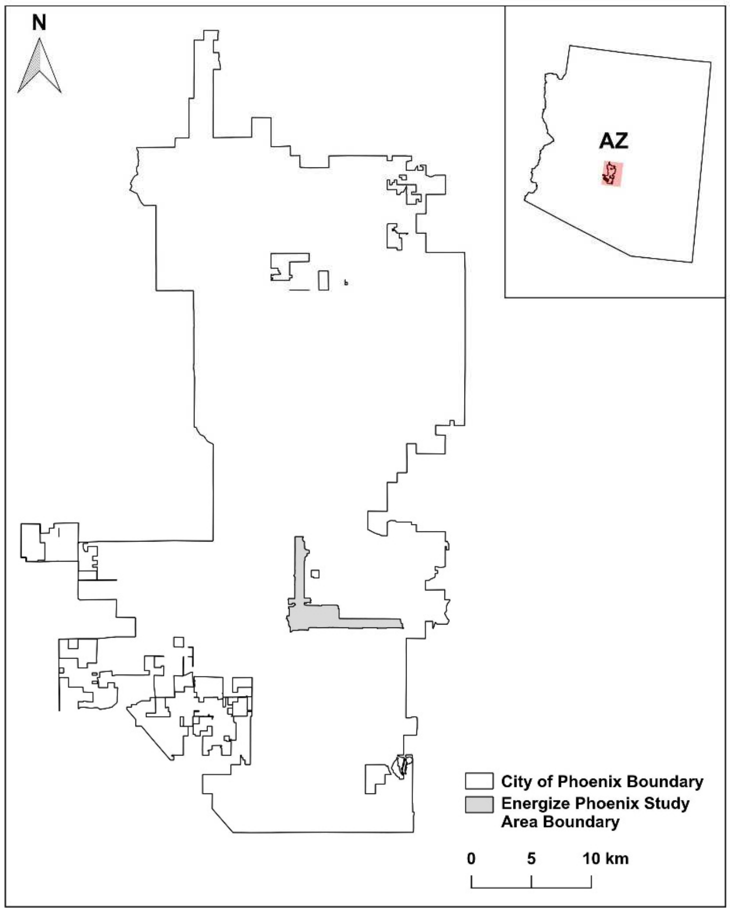

Figure 2A-1 Study area of light rail corridor in Phoenix for the Energize Phoenix program.

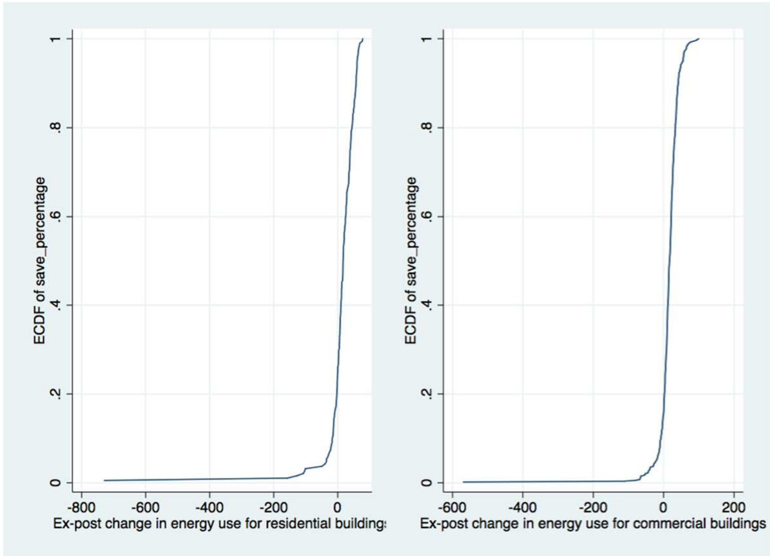

Figure 2A-2 Cumulative distribution function for ex-post change in electricity consumption of residential buildings and commercial buildings.

Note:

Histograms of ex-post change in electricity consumption are obtained based on the descriptive data. ECDF refers to a nonparametric cumulative distribution function. The large variability of the histogram indicates that there is a large uncertainty associated with the savings. The probability that the building has a percentage saving exceeding 8% (the average estimated savings) is 37% for residential buildings. 40% of the commercial buildings have savings of over 12%. There are a few extremely low values in the histograms for unexplained reasons. One of the residential buildings has post-treatment electricity consumption eight times higher than pre-treatment use and one commercial building has post-treatment consumption six times higher than pre-treatment consumption.

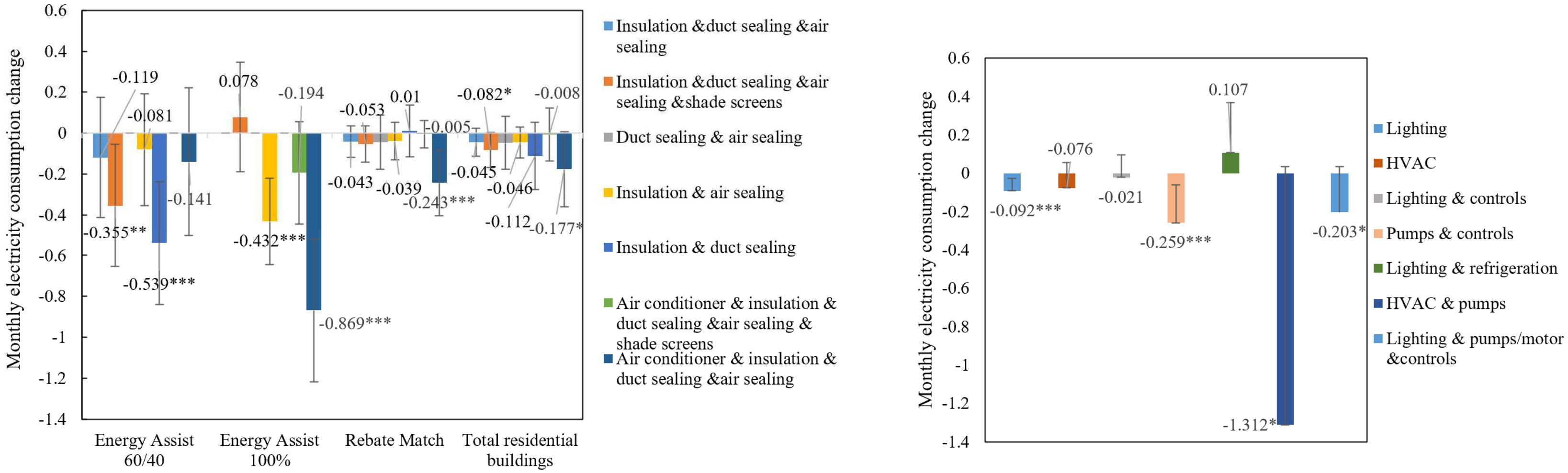

Figure 2A-3 Effects of retrofit bundles on electricity use for residential and commercial buildings.

Note:

The regression model is based on equation (2-2), where the treatment variable is the treatment of a retrofit bundle. The dependent variable is the natural log of monthly electricity use in kWh. The model includes building fixed effects and month-of-sample fixed effects. The error bars show the 95% confidence intervals. Monthly electricity consumption change is in log point. *** Significant at 1%level, ** significant at 5% level, * significant at 10% level.

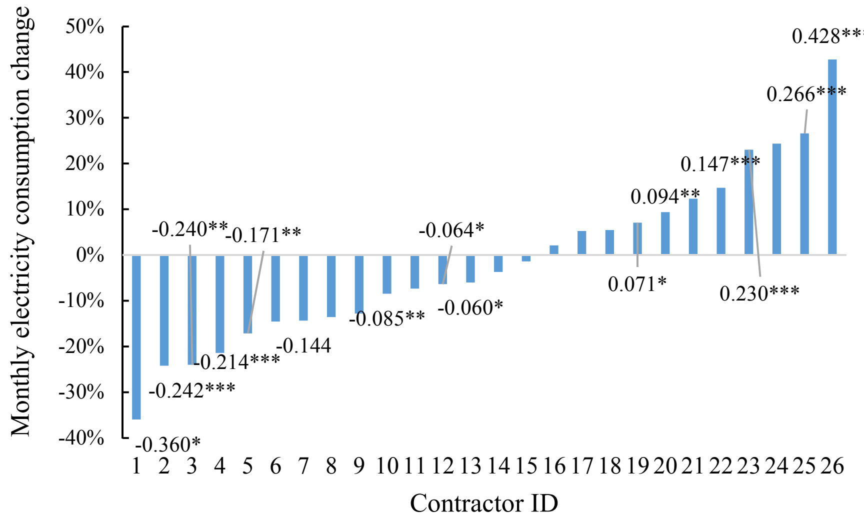

Figure 2A-4 Treatment effects on residential buildings with contractor impact.
Note:
The monthly electricity consumption change is in percentage. The regression model includes building fixed effects and month-of-sample fixed effects. The dependent variable is the natural log of monthly electricity use in kWh. Interaction terms of retrofits and contractor indicator variables are included. The contractor ID number indicates different contractors.

Table 2A-1 Retrofits and retrofit bundles for residential and commercial buildings

Panel A: Ratios of retrofits					
	Residential buildings			Commercial buildings	
	Energy Assist 60/40	Energy Assist 100%	Rebate Match		
Air conditioner	6/24	9/14	8/163	HVAC	33/636
Insulation	22/24	13/14	119/163	Lighting	437/636
Duct sealing	21/24	11/14	141/163	Refrigeration	15/636
Air sealing	19/24	10/14	142/163	Pumps/motors	28/636
Shade screens	5/24	9/14	37/163	Lighting controls	68/636
				Windows	25/636
Panel B: Percentage of retrofit bundles					
Insulation& duct sealing & air sealing	9/24	0/14	77/163	Lighting	401/636
Insulation & duct sealing &air sealing & shade screens	4/24	2/14	19/163	HVAC	28/636
Duct sealing & air sealing	0/24	0/14	16/163	Lighting & controls	16/636
Insulation & air sealing	2/24	1/14	7/163	Pumps & controls	9/636
Insulation & duct sealing	2/24	0/14	6/163	Lighting & refrigeration	9/636

Air conditioner & insulation & duct sealing &air sealing & shade screens	0/24	6/14	2/163	HVAC & pumps	2/636
Air conditioner & insulation & duct sealing & air sealing	3/24	1/14	2/163	Lighting & pumps & controls	4/636
Others	9/24	0/14	33/163	Others	167/636

Note:
[a] The denominator is the total number of buildings of the specific type (i.e., 24 for Energy Assist 60/40, 14 for Energy Assist 100%, 163 for Rebate Match, and 636 for commercial buildings). The numerator is the number of buildings that received the type of retrofit listed in each row.
[b] A bundle of retrofits means the combination of retrofits chosen by the participants.

Table 2A-2 Building attributes for control and treatment buildings.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Panel A: Residential buildings					
Control buildings					
Wall type	159	1.597	0.492	1	2
Floors	159	1.403	0.492	1	2
Total square footage	159	1885.535	437.171	1000	2100
Window square footage	159	319.811	139.678	94	468
No. of occupants	159	2.403	0.492	2	3
No. of bedrooms	159	3	0	3	3
CFM50[a]	159	4402.063	1841.962	808	5822
Treatment buildings					
Wall type	5,785	1.622	0.569	1	3
Floors	5,785	1.174	0.379	1	2
Total square footage	5,728	1744.867	561.927	125	3775.062
Window square footage	5,785	267.740	122.649	73	747
No. of occupants	5,785	2.195	0.904	1	7
No. of bedrooms	5,653	2.931	0.557	1	5
CFM50	5,771	2655.657	1419.220	150	7656
Panel B: Commercial buildings					
Control buildings					
Actual square footage	451	373.614	767.240	0	3,000
No. of employees	152	11.375	8.708	4	30
Total open hours	23	59	0	59	59
Self-reported years of buildings	151	15.781	4.758	6	20
Treatment buildings					
Actual square footage	34,039	39671.28	130,319.9	0	1,873,080
No. of employees	10,634	99.334	404.471	0	3600
Total open hours	4,769	67.843	39.743	0	275
Self-reported years of	10,411	20.457	16.930	0	98

buildings

Table 2A-3 Effects of different types of retrofit on electricity use using building× year fixed effects.

	Residential buildings				Commercial buildings	
	Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total	Total	
Electricity price	0.216	11.779**	10.017***	9.026***	Electricity price	4.514***
	(5.268)	(4.168)	(1.923)	(1.615)		(1.329)
Air conditioner	0.146	-0.625	-0.166**	-0.085	HVAC	0.010
	(0.135)	(0.500)	(0.083)	(0.073)		(0.044)
Insulation	-0.299**	1.810***	0.109*	0.102*	Lighting	-0.055***
	(0.136)	(0.555)	(0.062)	(0.057)		(0.020)
Duct sealing	0.014	-0.893***	-0.068	-0.039	Refrigeration	-0.025
	(0.156)	(0.262)	(0.066)	(0.058)		(0.093)
Air sealing	-0.114	-1.478**	-0.087	-0.134**	Pumps/motors	-0.080
	(0.103)	(0.523)	(0.069)	(0.054)		(0.060)
Shade screens	0.007	0.813***	0.070	0.067	Controls	-0.007
	(0.156)	(0.179)	(0.053)	(0.050)		(0.039)
					Windows	-0.147***
						(0.053)
CDD	0.040***	0.019***	0.021***	0.023***	CDD	0.013***
	(0.008)	(0.006)	(0.003)	(0.003)		(0.000)
HDD	0.011***	0.013	0.015***	0.014***	HDD	0.002**
	(0.003)	(0.008)	(0.002)	(0.002)		(0.001)
No. of observations	1234	799	7906	9939		34736
R^2	0.798	0.776	0.769	0.768		0.465

Note:
The dependent variable is the natural log of monthly electricity consumption in kWh.
All columns include month-of-sample fixed effects and building×year fixed effects.
The standard error (in parentheses) is clustered at the building level.
* Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Table 2A-4 Overall effects of retrofits on electricity use with control buildings

	Residential buildings	Commercial buildings

	Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total	Total
Electricity price	10.085	14.345***	13.653***	13.434***	-13.312***
	(6.532)	(3.746)	(1.713)	(1.516)	(2.851)
Retrofit	-0.228**	0.063	-0.040	-0.047**	-0.114***
	(0.110)	(0.130)	(0.025)	(0.023)	(0.028)
CDD	0.005	-0.032***	-0.001	-0.003	-0.009
	(0.019)	(0.007)	(0.004)	(0.004)	(0.006)
HDD	0.112**	0.035	0.082***	0.078***	-0.025*
	(0.050)	(0.044)	(0.016)	(0.015)	(0.014)
No. of observations	1324	926	10210	12460	35505
R^2	0.733	0.737	0.722	0.720	0.361

Note:
The dependent variable is the natural log of monthly electricity consumption in kWh. All columns include building fixed effects and month-of-sample fixed effects. The standard error (in parentheses) is clustered at the building level.*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 2A-5 Building attributes before and after propensity score matching.

	Before matching		After matching	
	Treated buildings	Control buildings	Treated buildings	Control buildings
Residential buildings				
Low-income households (=1 if yes)	0.070	0.055	0.070	0.070
	(0.256)	(0.229)	(0.256)	(0.256)
Average monthly pre-treatment summer electricity consumption (kWh)	1,606.95	1,618.22	756.79	1,701.86
	(726.90)	(694.26)	(726.90)	(720.27)
Average monthly pre-treatment winter electricity consumption (kWh)	756.79	770.51	1,607	806.17
	(481.62)	(446.36)	(481.62)	(472.07)
Commercial buildings				
Office (=1 if yes)	0.324	0.159	0.324	0
	(0.469)	(0.3674)	(0.468)	(0)
Average monthly pre-treatment summer electricity consumption (kWh)	104004.5	52441.05	132145.3	214906.8
	(375789.5)	(145012.9)	(453832.9)	(289777.4)
Average monthly pre-treatment winter	132145.3	66875.32	104004.5	183637.9

electricity consumption (kWh)				
	(453832.9)	(179519)	(375789.5)	(244867.1)
Square footage	63795.66	32145.95	55600.67	222440.3
	(163810.6)	(76624.69)	(149176.1)	(140361.6)

Note:
The standard deviation is in parentheses. For commercial buildings, continuous variables are re-categorized using tertiles to get balanced propensity score. There are 45 different residential control buildings matched for 186 treated buildings and 10 commercial control buildings matched for 544 treated commercial buildings.

Table 2A-6 Overall effects of retrofits using propensity score matching.

	Residential buildings				Commercial buildings
	Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total	Total
Electricity price	10.525*	12.902***	12.392***	12.130***	-11.620***
	(6.140)	(3.495)	(1.274)	(1.063)	(3.136)
Retrofit	-0.141	-0.173**	-0.019	-0.040**	-0.083***
	(0.087)	(0.072)	(0.021)	(0.019)	(0.016)
CDD	0.009	-0.036***	-0.001	-0.003	-0.021***
	(0.011)	(0.006)	(0.003)	(0.002)	(0.004)
HDD	0.079**	0.079***	0.066***	0.064***	-0.053***
	(0.031)	(0.027)	(0.012)	(0.010)	(0.011)
No. of observations	1486	1565	16293	19344	40927
R^2	0.754	0.794	0.735	0.733	0.320

Note:
The dependent variable is the natural log of monthly electricity consumption in kWh. All columns include building fixed effects and month-of-sample fixed effects. The standard error (in parentheses) is clustered at the building level. The number of observations is not double of the number of observations in Table 2-2 because some treated buildings are not matched and thus are dropped. In addition, not all the buildings have data for all the months. The control buildings do not necessarily have the same number of observations as the treated buildings. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Appendix 2B: Impacts of building attributes on treatment effects

To assess the impacts of building attributes on the effects of retrofits, interaction terms of retrofits and building attributes are added into the model (2), described by equation (B1):

$$In(Electricity_{it}) = \boldsymbol{\alpha}'\boldsymbol{T}_{it} + \beta P_{it} + \delta_1 CDD_t + \delta_2 HDD_t + \boldsymbol{\theta}'\boldsymbol{T}_{it}\boldsymbol{B}'_{it}$$

$$+\eta_i + \xi_t + \varepsilon_{it} \qquad \text{(B1)}$$

where $\boldsymbol{B}_{it}$ is a vector of building attributes, such as the number of occupants, wall type, and building square footage. The interaction terms $\boldsymbol{T}_{it}\boldsymbol{B}_{it}^{'}$ reflect the impacts of building attributes on the retrofit effects.

Building attributes such as square footage, the number of occupants, roof insulation, attic ventilation, and air leakage interact with retrofits on treatment effects (Table 2B-1). For example, the negative interaction terms indicate that insulation retrofits could effectively address poor roof insulation by improving the insulation. Houses with wood frames tend to impede insulation retrofits from working properly. Duct sealing retrofits also save more with better roof insulation. If the attic ventilation is in better condition, air sealing around the walls is less likely to lead to electricity savings. This essay also explores how building attributes interact with the treatment effects by incorporating factors such as the number of employees, owner-occupied or tenant-occupied, and whether it is small a business or not. Most interaction terms are small in magnitudes or not statistically significant (p>0.10). However, there are some significant interaction terms. For example, the interaction terms of pump retrofit and the business being a small business are statistically significant. This is intuitive because the energy consumed by pumps contributes significantly to the energy use of a small business and pump retrofits could have great potential in saving energy.

Table 2B-1 Impact of building attributes on treatment effects for residential buildings.

	Air conditioner	Insulation	Duct sealing	Air sealing	Shade screens
Square footage	-0.007	0.0002	0.00001	-0.00007	-0.00005
	(0.007)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
No. of occupants	1.930	-0.069	-0.006	0.074	0.020
	(1.946)	(0.062)	(0.075)	(0.088)	(0.088)
Window square footage	-0.004	0.0009	-0.0001	-0.0009	0.0001
	(0.003)	(0.0007)	(0.0003)	(0.0007)	(0.0007)
Wood frame wall type [a]	N/A[b]	0.251*	0.018	-0.210	-0.011
		(0.137)	(0.146)	(0.151)	(0.123)
CFM50[c]	-0.001	0.00002	-0.000008	-0.000007	-0.00002
	(0.001)	(0.00005)	(0.00004)	(0.00004)	(0.00003)
Window U value [d]	5.200	0.295	-0.024	-0.106	0.248
	(5.826)	(0.302)	(0.449)	(0.423)	(0.401)
Condition of roof insulation [e]	N/A	-0.341*	-0.446**	0.589**	0.133

		(0.199)	(0.220)	(0.266)	(0.204)
Attic ventilation f	2.307	-0.271	-0.027	0.334*	0.010
	(2.750)	(0.215)	(0.165)	(0.200)	(0.156)

Note:
Coefficients are for the interaction terms of the retrofits of each column and the building attributes of each row. The dependent variable is the natural log of monthly electricity use in kWh. All columns include building fixed effects and month-of-sample fixed effects. The regression includes treatment dummies. The number of observations is 7644 and R^2 is 0.725. * Significant at 10% level. ** Significant at 5% level. ***Significant at 1% level.
[a] Base case: masonry and other frames.
[b] Variable dropped due to multicollinearity.
[c] CFM50: airflow needed to create a change in building pressure of 50 Pa, which indicates air leakage.
[d] Measure of the rate of heat transfer of the entire window assembly; the window insulation is better with a lower U value.
[e] Base case: poor roof insulation.
[f] Base case: poor attic ventilation.

Appendix 2C: Robustness check with respect to alternative vacancy indicator and retrofit month window

Table 2C-1 shows that the results using 1 month or 2 months as the window of retrofits are very similar. The installation time could vary from a few hours to a weekend. However, the overall time is not long, according to the program manager. The month of installation is mixed with before- and after- retrofits data. Therefore, at least one month of data should be dropped. I drop one-month data for the main analysis in this study. Upon applying the 2% and 5% lowest electricity consumption as the vacancy indicator, the energy savings for commercial buildings seem to change. This indicates there are some smaller consumers and simply dropping them may influence the analysis.

Table 2C-1 Robustness checks using alternative vacancy indicator and retrofit month window

	Residential buildings				Commercial buildings
	Energy Assist 60/40	Energy Assist 100%	Rebate Match	Total	Total
Retrofit (dropping 1% + 1 month of retrofits)	-0.302*** (0.103)	-0.041 (0.116)	-0.069** (0.031)	-0.082*** (0.026)	-0.125*** (0.030)
Retrofit (dropping 1% + 2 months of retrofits)	-0.304** (0.113)	-0.108 (0.129)	-0.066* (0.034)	-0.080*** (0.028)	-0.125*** (0.033)
	-0.386***	0.090	-0.064**	-0.076**	-0.119***

Retrofit (dropping 2% + 1 month of retrofits)	(0.110)	(0.168)	(0.032)	(0.030)	(0.029)
Retrofit (dropping 2% + 2 months of retrofits)	-0.386*** (0.125)	-0.090 (0.224)	-0.049 (0.037)	-0.064* (0.034)	-0.119*** (0.032)
Retrofit (dropping 5% + 1 month of retrofits)	-0.224* (0.115)	-0.111 (0.087)	-0.058** (0.024)	-0.071*** (0.021)	-0.109*** (0.029)
Retrofit (dropping 5% + 2 months of retrofits)	-0.233* (0.127)	-0.190* (0.090)	-0.052** (0.026)	-0.068*** (0.022)	-0.109*** (0.032)

Note:
Each row is a regression model, with electricity price, cooling degree days, and heating degree days included. The dependent variable is the natural log of monthly electricity use in kWh. h. All columns include building fixed effects and month-of-sample fixed effects. The standard error (in parentheses) is clustered at the building level. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Chapter 3: Time-of-Use Electricity Pricing and Residential Low-carbon Energy Technology Adoption

3.1 Introduction

Energy efficiency and solar energy are two low-carbon measures promoted by policymakers to reduce residential energy consumption from fossil fuels and the associated greenhouse gas emissions. Various policies and financial incentives (e.g., tax credits, direct rebates, etc.) exist to encourage the adoption of these low-carbon technologies. For example, the cost of typical financial incentives (including direct rebates and tax credits) for the adoption of a solar panel system is \$5,500~\$9,000 (Solar Energy Industries Association, 2014; Hughes and Podolefsky, 2015; Gillingham and Tsvetanov, 2019). However, despite these costly incentives, the penetration of energy efficiency and solar energy is still relatively low for many years. Many organizational, behavioral, and market factors have been analyzed in the existing literature to explain their low adoption level (Hirst and Brown, 1990; Margolis and Zuboy, 2006; Timilsina et al., 2012; Zhang et al., 2012; Gillingham and Palmer, 2014; Ramos et al., 2015). 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).

Time-Of-Use (TOU), one of the most widely adopted dynamic pricing programs, charges different electricity prices depending on the time of the day, namely, 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 baseload. In addition, reducing peak load helps utilities maintain 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 essay focuses on another potential positive welfare impact of TOU—its correlation with low-carbon technology adoption (energy efficiency and solar panel installation).

Figure 3-1 shows how electricity prices correspond 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). 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 happens during peak hours when electricity prices are also high. Naturally, this correlation between prices and savings might incentivize consumers to adopt energy efficiency and solar panels if they are on TOU plan. However, there is little empirical analysis to quantify the correlation between TOU and adoption of these technologies. This essay provides the first empirical evidence of such correlation and fills the gap in existing literature.

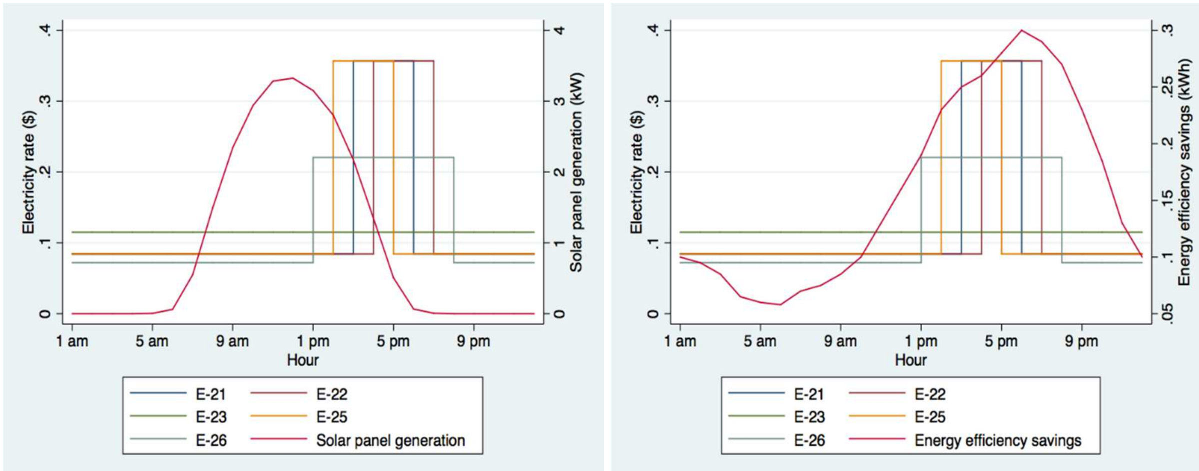

Figure 3-1 Hourly energy efficiency savings and solar electricity generation
Note:
E-21, E-22, E-23, E-25, and E-26 are different price plans as detailed in Table 3-1. E-23 is a non-dynamic pricing plan while the other plans are TOU plans. The price levels in the figure are prices during July and August. The energy efficiency savings are calculated based on data in July and August. The unit of solar panel generation is kW while for energy efficiency energy savings the unit is kWh.

3.2 Literature Review

This study fills the gap in the existing literature by 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 the "energy efficiency gap" (Jaffe and Stavins, 1994). The 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 costs, technology risk and complexity (Drury et al., 2012), information barriers during the information-search process (Rai et al., 2016) and a lack of incentives. However, rate design is often a factor missed in the existing empirical studies (Novan and Smith, 2018). This essay contributes to this strand of studies by exploring empirically whether rate design is correlated with solar panel adoption and energy efficiency adoption.

Second, there have been many studies focusing on the impacts of TOU rates on energy consumption behaviors. 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 behaviors (Torriti, 2012; Faruqui et al., 2014). The load shifting behaviors could be a result of technology adoption (e.g., demand-side management technology and renewable energy technology), or purely shifting consuming activities such as watching TV or washing clothes from peak to off-peak hours. This essay contributes to this strand of studies by examining whether TOU is correlated with energy technology adoption, which can serve as one underlying explanation for the observed load shifting behaviors in existing studies.

Third, despite simulations or modeling exist to study 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 rate structures (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 the 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 incentives 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. This essay will provide an empirical analysis. An empirical study on the correlation between TOU and solar adoption can help verify the simulation studies. It can also further assist policymakers in choosing the appropriate rate designs that better reflect the social cost of providing electricity and also potentially encourage the adoption of energy efficiency or solar panels (Ong et al., 2010).

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

I do not claim that the current finding of the correlation between TOU and technology adoption is causal, although I 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 the dataset, for all solar consumers, only 7 solar consumers (less than 1.4% solar consumers) switched to TOU after they adopted solar panels. I dropped these 7 solar consumers to help avoid reverse causality. Also, on average, solar consumers adopted solar panels several years after they enrolled in TOU pricing, and this helps reduce the possibility of reserve causality temporally. 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 they are also more likely to adopt energy efficiency and solar panels. If these households have specific characteristics unobservable to us such as environmental awareness and knowledge on energy usage, there is a potential of self-selection bias. I apply a matching approach and include a rich set of covariates to help deal with such self-selection bias. For a customer that is on TOU pricing, I find a control customer that is similar in terms of home and socio-economic characteristics and that is not on TOU pricing. Additionally, in the main analysis, I use the adoption of programmable thermostats as a proxy for environmental awareness to partially reduce the selection bias.

3.3 TOU Pricing Plans

This study focuses on the residential consumers from the Salt River Project (SRP), one of the largest electric utilities in Arizona. The temperature in Phoenix, Arizona is high in the summer and has a large electricity demand for cooling during peak times in the summer, which contributes to the development of dynamic pricing plans in Arizona (Kirkeide, 2012). Moreover, Arizona is a good case for studies on solar panel installation because it is one of the top three solar states in the United States. It has a large installed capacity and large per capita cumulative solar electric generating capacity (Qiu et al., 2017b; Qiu et al., 2019).

The empirical data used in this essay is provided by the Salt River Project (SRP), one of the largest electric utilities in Arizona. I use data from the Residential Equipment and Technology (RET) survey conducted by SRP in 2014. Residential consumers were randomly 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 that includes the timing of solar panel adoption for each solar customer and a subset of energy-efficient AC installations, as well as types of electricity rates that customers enrolled.

In December 2014, there was a major change in the net metering policy of SRP. Before 2014, SRP consumers with solar panels are under a self-generation plan which charges a fixed monthly service fee, a demand charge, and an hourly energy price (lower than the standard rate). SRP consumers started to have net metering after policy change. In the net metering plan, the energy generation in kWh is subtracted from the total consumption to have a net number. However, in this essay, since the RET survey was conducted in early 2014, the impact of the electricity rate is estimated without the influence of net metering. If there were net metering, the impact of price plans on solar adoption will be expected to be larger (Gautier and Jacqmin, 2020).

In 2014, there were six types of electricity rates, numbered from E-21 to E-26. The price plans listed in Table 3-1 show the details of the per kWh charges. The monthly service charge is the same for all rate plans and there is no demand charge. Among them, E-23 and E-24 are non-dynamic rates (flat rates) while the rest are TOU rates. I drop households in the M-power program (E-24 plan) because E-24 is a prepaid electricity plan. It 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 conditioners, room air conditioners, and solar panels. The participants were asked to report whether they replaced any appliance during the last 3 years and whether the appliances were replaced by energy-efficient alternatives, i.e., Energy Star certified appliances. Energy Star appliances are considered more energy efficient compared to uncertified ones because the certified products exceed the federal energy efficiency standard. The survey also includes questions about 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 dwellings are covered in this study, including single-family homes, mobile homes, and apartments/condos/townhouses.

3.4 Methodology

3.4.1 Summary Statistics

I focus on energy-efficient air conditioners because the electricity use from ACs also increases the fastest among all appliances (Boomhower and Davis, 2019). An understanding of the relationship between TOU and adoption of energy-efficient ACs can provide insights into the influences of TOU on other appliances. Figure 3-2 provides a descriptive figure which 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 3-3 is a map showing the uptake of solar panels, energy-efficient ACs, and TOU rates at the zip code level. The adoption of energy-efficient room air conditioners is also included in this essay because this should be useful for policymaking in developing countries where room air conditioners are more widely adopted compared to central air conditioners.

Table 3-1 Salt River Project TOU and standard residential tariffs

Pricing plan	Name	Division	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	

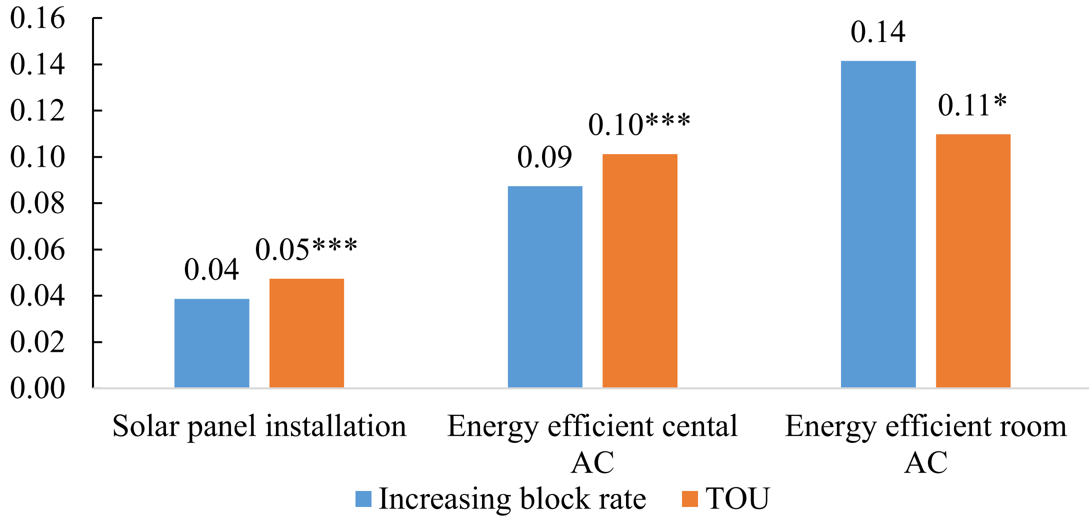

Figure 3-2 Adoption of energy-efficient air conditioners and solar panels
Note:
The vertical axis is the saturation level (with the range from 0 to 1) of the energy efficient air conditioners or solar panels; the denominators for the saturation level calculation are the number of consumers who reported whether they have the technologies or not; *** means statistically different by t-test at 1% level; * is at 10% level.

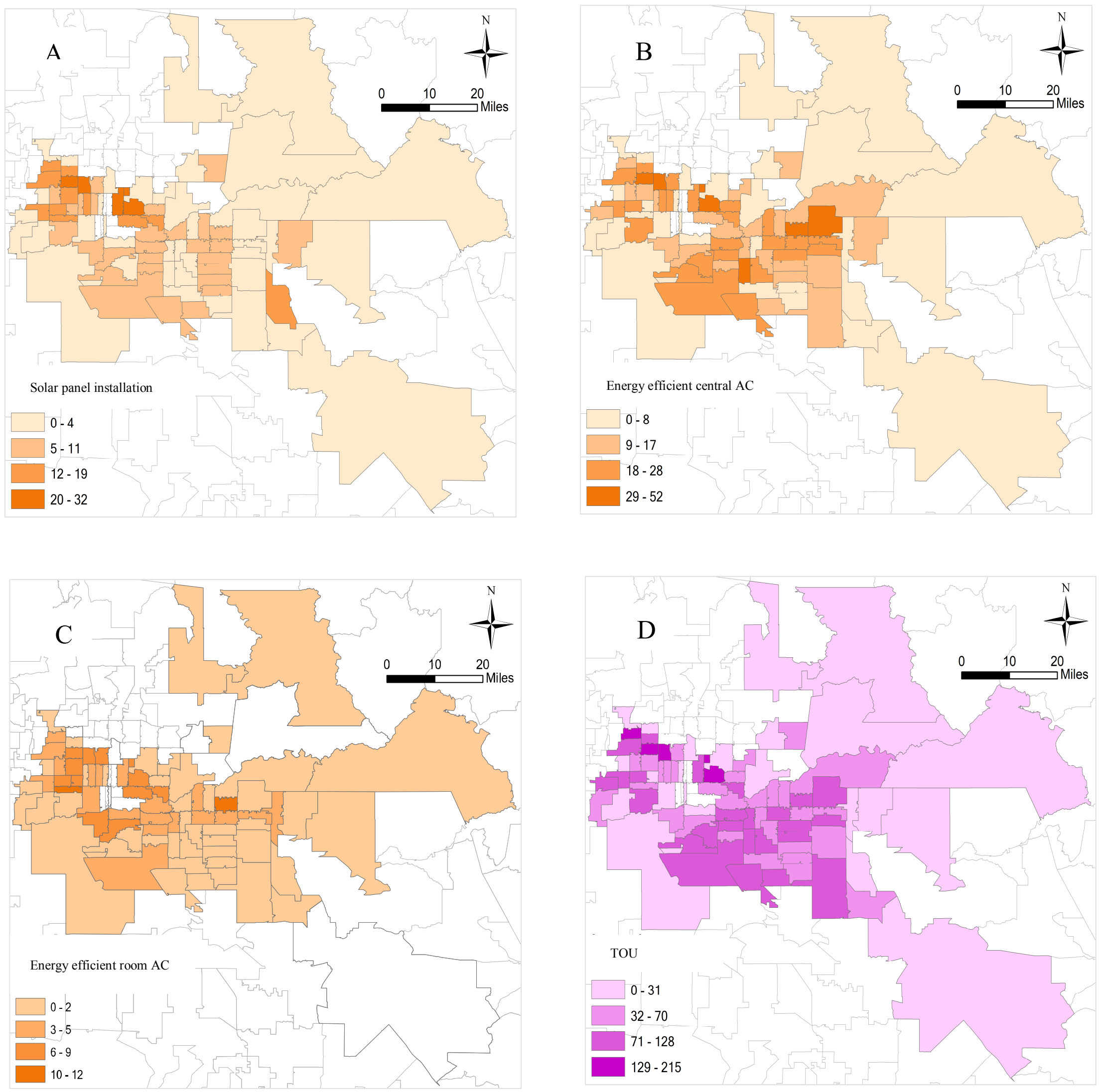

Figure 3-3 Uptake of solar panels (A), energy efficient central AC (B), energy efficient room AC (C) and TOU rates (D)
Note:
Color indicates number of adoptions based on the survey responses.

The social-demographics and housing characteristics between TOU consumers and flat rate consumers are different (Table 3-2). TOU consumers have higher monthly electricity usage, higher household income, and larger square footage. Their houses are more likely to be primary residences rather than seasonal residences, and the houses are more likely to have swimming pools and programmable thermostats. Additionally, the non-TOU households have a longer vintage of the house and an older household head.

However, a reverse causality problem is not a major concern in this study although it is possible that some consumers first adopt solar panels or energy-efficient AC units and then switch to TOU plans. For all 558 solar consumers in the RET survey, only 7 solar consumers switched to TOU after they adopted solar panels. I dropped these 7 solar consumers to help avoid this reverse causality. In addition, according to the SRP's customer-level data, the solar consumers adopted solar panels five years, on average, 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 the dataset happens after 2011 while the average timing for TOU enrollment is between 2007 and 2008. Because of this long lag (several years) between TOU enrollment and solar adoption, it is unlikely that TOU consumers are very forward-looking and consider adopting solar panels when making the decision on enrollment in TOU.

3.4.2 Matching approaches

Usually, randomized control trials and natural experiments are ideal strategies to evaluate a causality relationship in empirical studies (Alberini and Towe, 2015). However, given only observational data are available in this study, I use a matching approach to approximate a randomized experiment (Stuart, 2010). The control group is matched with the treated group, and these two groups are very similar based on all 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 also applied more frequently in recent studies (Stuart, 2010).

Propensity score matching and coarsened exact matching are different in that they represent two known classes of matching (Rubin, 1976; Iacus et al., 2011). Propensity score matching aims at "equal percent bias reducing" (i.e., makes the means of covariates closer by the same amount) and coarsened exact matching aims at "Monotonic Imbalance Bounding'' (i.e., guarantees a reduction of imbalance). Propensity score matching is based on the probability of being treated (Dehejia and Wahba, 2002), and coarsened exact matching coarsens the variables into strata and prunes both the treated and control variables (Iacus, et al., 2012). The matching solution for propensity score matching is ex-ante and balance is ex-post. Balance checking is necessary for propensity score matching. 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 $SMD = \frac{\overline{X}_{Treat} - \overline{X}_{Control}}{\sqrt{(S^2_{Treat} + S^2_{Control})/2}}$ and $VR = \frac{S^2_{Treat}}{S^2_{Control}}$, where $\overline{X}$ is the mean and s^2 is the variance. The 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 a good balance (Rubin, 2001). All control variables including the demographic and housing characteristics are used as matching variables, as listed in Table 3-2.

Table 3-2 Summary statistics of building characteristics and demographics for TOU and flat rate

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

Note:
[a] The number of energy-efficient central AC adoption is smaller than the number of solar panel installations because fewer people reported on this variable;

[b] This is the number of people that reported whether they adopted energy-efficient room ACs or not. There are 11,882 households without room air conditioners and thus adoption of energy-efficient room ACs 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.

3.4.3 Basic model specification

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

$$y_i = \begin{cases} 1 \; if \; y_i^* > 0 \\ 0 \; otherwise \end{cases} \quad (3\text{-}1)$$

$$y_i^* = \beta_0 + \beta_1(TOU_i) + \beta_2\boldsymbol{X_i} + \varepsilon_i \quad (3\text{-}2)$$

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 $\boldsymbol{X}$, I use the adoption of programmable thermostats as a proxy for environmental awareness. One might argue that the adoption of programmable thermostats itself is endogenous. However, this essay does not focus on interpreting the coefficient for programmable thermostat adoption. This variable only serves 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 thermostats, the part of the error terms 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 the dataset because all consumers are served by the same utility and the same incentives are provided to all consumers. Although other characteristics such as the shade conditions and roof directions might also impact solar panel adoption, these impacts are assumed to be random to the adoption of TOU pricing and are uncorrelated with it. Therefore, they do not interfere with the estimation of TOU's impacts.

3.5 Econometric Analysis

3.5.1 Coarsened exact matching

Each column in Table 3-3 is a single probit regression on the matched control and treatment consumers. Coarsened exact matching is applied. Models in columns (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 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 3-4, 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.

Table 3-3 shows that there is a positive correlation between TOU and solar panel installation. There is no evidence that TOU consumers are also more likely to adopt energy-efficient central ACs or room ACs. The coefficients on TOU for energy-efficient ACs 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 $\partial Prob(y_i=1)/\partial TOU_i$ for a reference individual. The mean of the solar adoption variable in the sample is 0.043. Thus 1.4 percentage point increase equals a 32.5% (1.4/4.3=32.5%) increase on average in solar panel adoption.

Table 3-3 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)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
	Probit model	Probit model	Probit model	Marginal effect	Probit model	Probit model	Probit model	Marginal effect	Probit model	Probit model	Probit model	Marginal effect
TOU	0.143 (0.093)	0.197** (0.100)	0.176* (0.098)	0.014* (0.007)	0.091 (0.063)	0.099 (0.065)	0.087 (0.064)	0.015 (0.011)	0.157 (0.187)	0.112 (0.208)	0.062 (0.265)	0.010 (0.041)
N	3,947	3,763	3,200	3,200	4,245	4,078	4,039	4,039	431	413	256	256
Socio-demographic & home characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Area (zip codes)	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
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	

Note:
[a] The matching is acceptable when the multivariate L1 distances reduces, which indicates the imbalance is reduced after matching;
[b] Variable is dropped because it predicts failure perfectly;
Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

Table 3-4 Weighted means[a] and standard errors of matching variables for TOU and non-TOU consumers using coarsened exact matching (analysis of solar panel installation)

Variable	Before matching				After matching			
	Non-TOU		TOU		Non-TOU		TOU	
	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)
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)

Note:
[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 $\frac{m_C}{m_T} \cdot \frac{m_T^s}{m_C^s}$ 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.

The 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 rates with the peak hours that coincide more with solar generation will benefit solar consumers more (McLaren et al., 2015). Therefore, TOU rates provide indirect incentives for adopting solar panels. The economic benefits of solar installation are expected to be even larger when TOU is coupled with net metering (Darghouth et al., 2011) or battery storage. Except for the possibility that larger savings will be obtained after combining TOU and solar panels, there are two other possibilities to explain the impact of TOU on solar adoption. First, TOU helps the consumers gain more net benefits, which may enable the consumers to use the money to further invest in green technologies such as solar PV. However, according to existing studies, the net savings from TOU are comparatively small. Savings are about 2.2% for residential consumers on their electricity bills from TOU (Torriti, 2012) and 5-6% for commercial consumers (Qiu et al., 2018). Given that the money saved is not large enough to compensate for the cost of installing PV, this possibility only partially explains the correlation. The second potential mechanism is through learning. Consumers could acquire additional information about the value of solar panels with the TOU adoption, which helps to reduce the uncertainty regarding the value of solar panels. The consumers could also change their appreciation for green technologies such as solar panels to get greater utility from past TOU adoption decisions.

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

3.5.2 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, and 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 3-5, are yielded with 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. During the process, the logit model is used to generate propensity scores. The results show TOU consumers are 0.9 percentage points more likely to adopt solar panels, and the coefficient is statistically significant at a 10% significance level. However, 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 3-6. All the variables in the control group are comparable to those in the treatment group after a balancing check using *SMD* and *VR*. Figure 3-4 confirms the common support assumption.

I further add on-peak prices into the model to test whether a higher peak price is correlated with the higher adoption of energy-efficient air conditioners and solar panels. Table 3A-1 in Appendix 3A shows that the coefficients on the interaction term between TOU and peak rate are not statistically significant both before and after matching. Theoretically, when the TOU peak rate is higher, there should be more adoption of solar panels, and the coefficient should have a positive sign. The possible reason 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 the positive relationship to be reflected in the regression.

Table 3-5 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)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
	Probit model	Probit model	Probit model	Marginal effect	Probit model	Probit model	Probit model	Marginal effect	Probit model	Probit model	Probit model	Mar effe
TOU	0.131**	0.120**	0.107*	0.009*	-0.001	-0.013	-0.027	-0.005	-0.074	-0.082	-0.137	-0.0
	(0.058)	(0.059)	(0.060)	(0.005)	(0.041)	(0.041)	(0.042)	(0.007)	(0.118)	(0.124)	(0.140)	(0.0
N	9,187	9,187	8,682	8,682	9,474	9,474	9,461	9,461	1,084	1,084	847	847
Socio-demographic and home characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Area (zip codes)	No	No	Yes	Yes[a]	No	No	Yes	Yes[a]	No	No	Yes	Yes
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	

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

Table 3-6 Mean of variables before and after matching in TOU and non-TOU consumers using propensity score matching (analysis of solar panel installation)

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

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

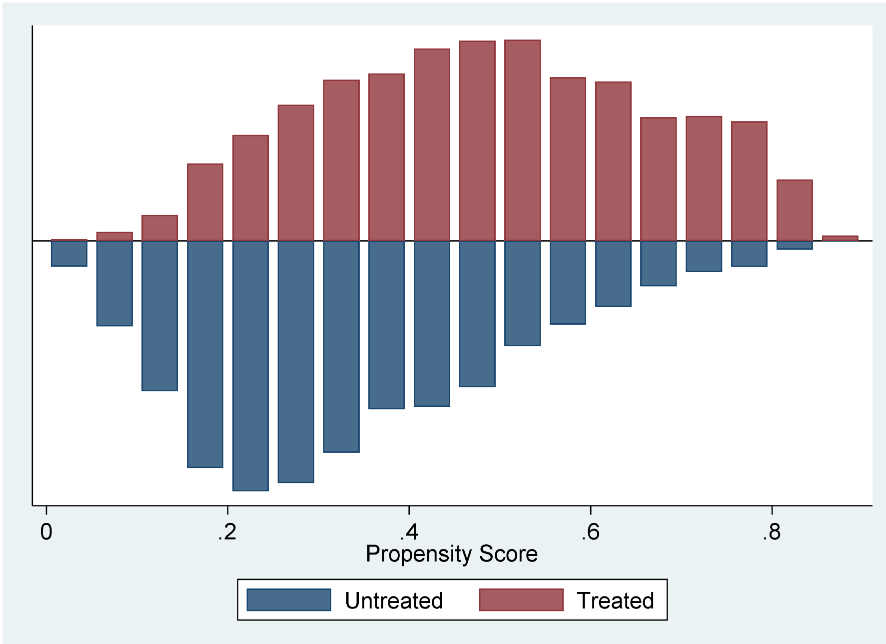

Figure 3-4 Check for common support for propensity score matching

3.5.3 Heterogeneity of TOU's correlation with solar panel adoption

This section includes an additional analysis with the renters excluded from the models (Table 3A-2 in Appendix 3A). The results are consistent with the analysis using a full sample, 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 finding that the owners are more likely to adopt low-carbon technologies (Gillingham et al., 2012; Krishnamurthy and Kriström, 2015). The main analysis has controlled for ownership by including a dummy variable of ownership status.

Separate analyses are done for mail versus web survey respondents (Table 3A-3) because it is possible that people's adoption of the internet could influence their adoption of green technologies such as solar panels (Comin and Rode, 2015). The results for participants of mail surveys are different from those of web surveys and the results based on mail surveys are more similar to the results of using all surveys. Also, the results are more statistically significant for mail survey respondents. This may be due to the difference in the sample size. Another potential explanation might be that the mail respondents are more permanent residents (i.e., more likely to own the house) and thus they are more likely to invest in expensive energy technologies such as solar panels.

Using the sample from propensity score matching, I also examine if the probability of solar adoption conditional on TOU pricing varies across other consumer/building characteristics (Appendix 3B). The characteristics include monthly electricity usage, household income, square footage of the property, persons in the household, property vintage (in years), and age of household head.

3.6 Robustness Checks

3.6.1 Multinomial logit model

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

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 $P_{ij} = P(y_i = j) = \frac{exp(\boldsymbol{w}_i' \gamma_j)}{\sum_{k=1}^{m} exp(\boldsymbol{w}_i' \gamma_k)}$. P_{ij} is the probability for an individual with characteristics $\boldsymbol{w}_i$ facing m (*m*=4) choices, and the covariates include the specific demographics and housing characteristics for individual *i*. The results of the multinomial logit model (Table 3-8) further indicate that TOU consumers are only more likely to install solar panels while TOU does not influence energy efficiency adoption.

Table 3-7 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%

Table 3-8 Adoption of energy efficiency or solar panels for treatment groups and control groups using the multinomial logit model

	Solar panels only	Energy-efficient central ACs only	Both solar panel and energy-efficient central ACs
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	-1673.4993		
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		

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

3.6.2 Bivariate probit

A bivariate probit model can also examine the correlation between TOU enrollment and the adoption of solar panels or energy efficiency: $y_i^* = \beta_0+\beta_1\boldsymbol{X_i} + \varepsilon_i$, $TOU_i^* = r_0+r_1\boldsymbol{X_i} + e_i$, and $\binom{\varepsilon_i}{e_i} \sim N\left[\binom{0}{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$. y_i and $\boldsymbol{X_i}$ have the same meaning as indicated in equation (3-2). ρ is the correlation coefficient. If ρ is significantly different from zero, the two decisions are interrelated. Table 3-9 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, the estimate of the correlation coefficient ρ is small and statistically insignificant for energy-efficient central ACs and room ACs, suggesting that the adoption of energy-efficient AC units is not correlated with TOU enrollment.

Table 3-9 Adoption of energy efficiency or solar panels and TOU pricing enrollment using a bivariate probit model [a]

	solar panel installation		Energy-efficient central AC		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)
ρ		0.075**		-0.008		-0.051
		(0.037)		(0.026)		(0.077)
N		9,187		9,474		1,084

Note:

[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; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

3.6.3 Matching using machine learning

The machine learning approach is adopted by using classification and regression trees (CART)-based propensity score model (see details in Appendix 3C). CART-based model uses decision trees or regression trees to incorporate additionality, interaction, and non-linearity (Lee et al., 2010). I use the boosted CART from the 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 ACs.

3.7 Monetary Valuation of TOU’s Association with Solar Adoption

3.7.1 Remaining issues and usefulness of the results

This essay applies a matching approach and controls for a rich set of covariates to try to identify the impact of TOU on solar panel adoption and energy efficiency adoption. The key assumption for a causal identification is that the factors influencing TOU enrollment and technology adoption are observable. Correlation might not indicate a causal relationship if there are unobservables that impact both TOU enrollment and solar or energy efficiency adoption. Examples of unobservables include consumers’ energy financial literacy and marketing information from local solar contractors.

Estimating the correlation (although not fully causal) between TOU and solar adoption is still meaningful. For example, if one of the unobservables is whether a household has encountered a local solar contractor that promotes the large benefit from solar under TOU, then the results would imply that such marketing campaigns 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 the programmable thermostat variable), then the results would imply that policymakers 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 further justify that the estimated correlation is causal, in the future, studies better data are needed such as information on exogenous variation impacting TOU enrollment. In terms of external validity, the 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.

3.7.2 Emission impact of TOU-correlated solar panel adoptions

In light of the correlation between solar panel adoption and TOU pricing, this section assesses the emission impacts associated with the additional solar panels. I first estimate how many solar panel installations are associated with TOU plan in 2014 in SRP's service territory. Next, I combine this estimation with the reduction in greenhouse-gas and environmental pollution emissions per installation of solar panel to obtain the overall emission impact. Estimates of emission reductions are estimated based on average hourly marginal damages of different pollutants (CO_2, SO_2, NO_X, and particulate matter) per kWh (Holland et al., 2016). Reduction in hourly electricity generation from solar panels is estimated using the PVWATTS model (Ong et al., 2010). The results are summarized in Table 3C-1. As Table 3C-1 indicates, the annual monetary equivalent of emission reduction is approximately $0.42 million.

3.7.3 Fiscal-subsidy equivalent of TOU impact

In this section, I conduct a back-of-the-envelope analysis to quantify the equivalent financial incentive that would achieve the same impact on solar adoption. TOU is associated with the same magnitude of impact as financial instruments such as rebates or tax credits of $2,070~$10,472[5]. 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% (based on (2,070+10,472)/(5,493+9,156)) of the current size of financial incentives for solar panels.

3.8 Conclusions and discussions

This essay explores the correlation between TOU and the adoption of solar panels and energy-efficient air conditioners among residential consumers. I find that consumers in Arizona on TOU plans are 27% on average more likely to install solar panels. However, this essay does not show a clear correlation between the TOU plan and energy

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[5] This back-of-the-envelope calculation should be treated as the upper bound because I impose a restrictive assumption including a linear relationship between monetary incentive and adoption rate.

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 3-1 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 with energy-efficient ones earlier, and the subsidies motivate the consumers to enter the market faster. Entering energy-efficient AC market only after a long period 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 this essay does 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 consumers regarding the benefit of TOU. When government or utilities implement educational or informational programs to consumers, they should bundle the information about the benefits from both solar and TOU together, which could potentially increase the adoption of both TOU and solar panels. From a cost-effectiveness perspective, combining TOU and solar in policy programs can also achieve a lower cost of adopting additional solar and TOU. Moreover, there could also be potential issues of redistribution effects from TOU, which could decrease social welfare eventually (Joskow and Wolfram, 2012). But according to Train and Mehrez (1994) and Action and Mitchell (1984), the net impact of some TOU plans on social welfare could still be positive.

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 due to increasing penetration of smart meters, the timing of energy savings can be more accurately tracked, which helps quantify the value of energy efficiency (Boomhower and Davis, 2019; Qiu and Kahn, 2018).

Despite the efforts in overcoming the threats to causal identification, due to limitations from this non-experimental cross-sectional dataset, there could still be remaining issues such as other omitted variables that could affect both TOU enrollment and technology adoption. However, even if the empirical finding of the correlation between TOU and solar adoption is not fully causal, quantifying such correlation is still valuable to policymakers. Both TOU and solar adoption could improve social welfare. TOU could enhance social welfare by aligning marginal electricity prices with marginal costs of electricity (Qiu et al., 2018; Train and Mehrez, 1994). A positive correlation between the two adoptions after controlling for other types of confounding factors implies that if policymakers 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. From a cost-effectiveness perspective, combining TOU and solar in policy programs can also achieve a lower cost.

3.9 Appendices

Appendix 3A: Figures and Tables

Table 3A1: Interaction of TOU and peak price

	Probit model for energy-efficient central ACs	Probit model for energy-efficient room ACs	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

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

Table 3A-2 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		
Propensity score matching		
TOU	-0.137	-0.031
	(0.140)	(0.164)
N	847	544

Table 3A-3 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 3B: Heterogeneity among building characteristics

Using the sample from propensity score matching, I 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 3-3 by introducing the interaction variable TOU*(variable of interest) into the specification. To reduce the number of combinations, I 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 straightforward. The coefficients are listed in Appendix Table 3B-1. Although each specification includes all of the variables included in column (3) of Table 3-5, for presentational ease I 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 3B-1.

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 the 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, lowering the probability of adoption. From a policymaking 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 3B-1 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

Note:
standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

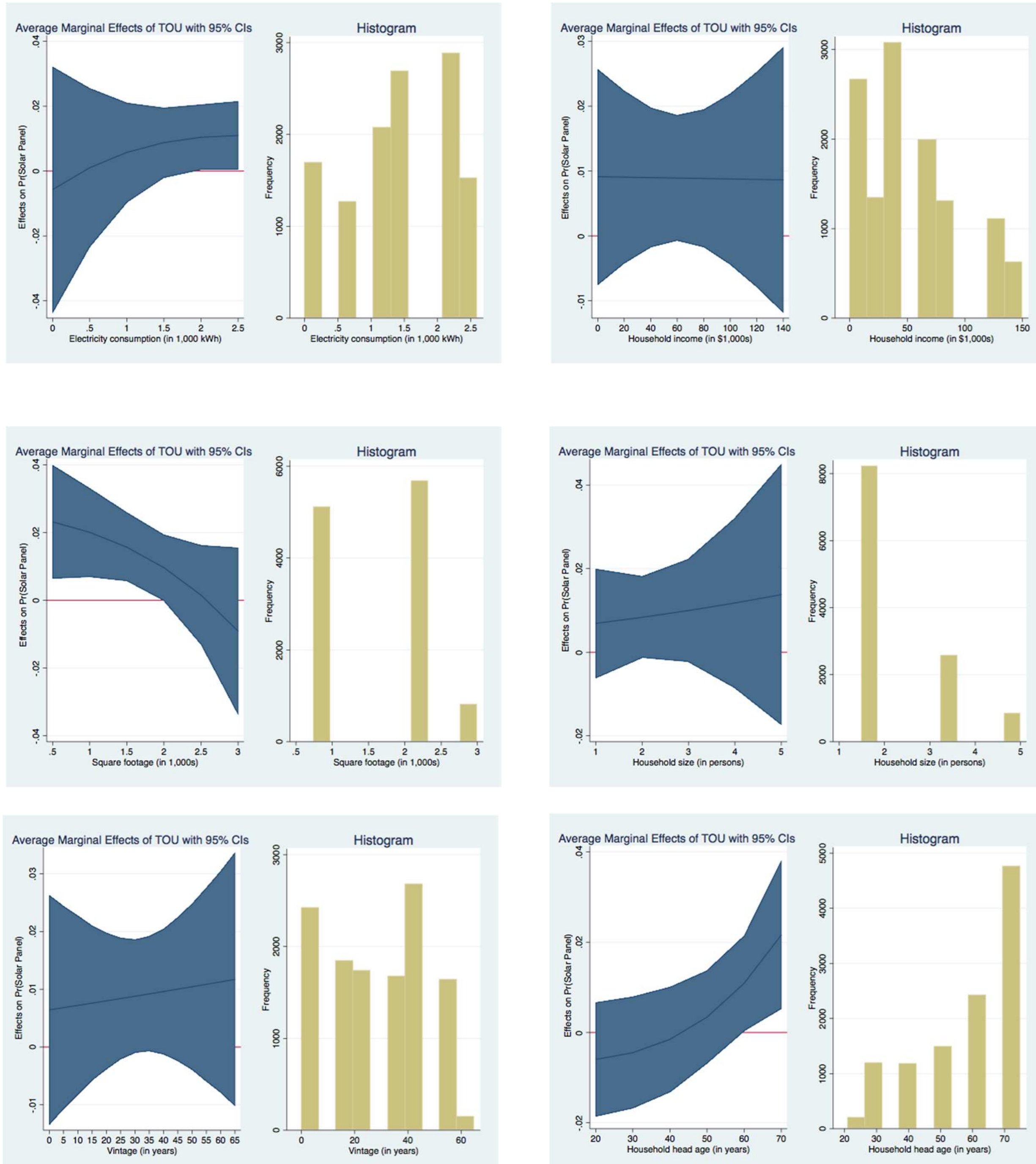

Figure 3B-1 Heterogeneity of marginal effects of TOU on solar panel installation
Note:
The variables of electricity consumption, household income, square footage, household size, vintage, and household head age in the survey are asked as categorical variables indicating ranges of values.

Appendix 3C: Machine Learning

Classification and regression trees (CART)-based propensity score model is applied, which is an alternative of logistic regression to estimate propensity scores. The 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 the 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 3C-1 shows the two stopping rules consistent with each other, indicating the results are not sensitive to the stopping rule. Table 3C-1 shows the balance table using standard effect sizes. Missing values of covariates are also balanced. Table 3C-2 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.

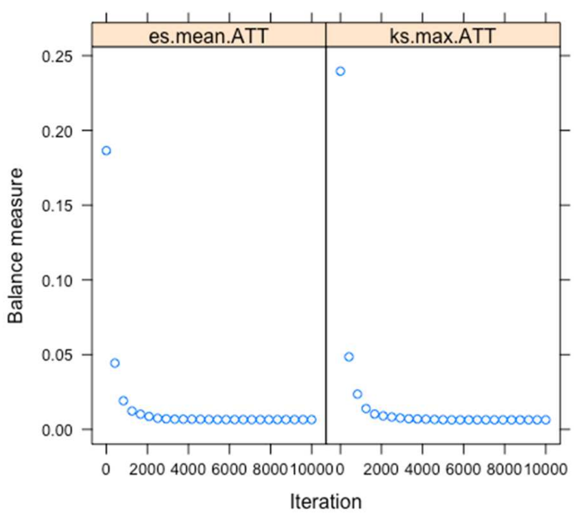

Figure 3C-1 Balance measure of stopping rules

Table 3C-1 Mean of variables before and after matching in TOU and non-TOU consumers (analysis of solar panel installation)

Variable	Before matching				After matching			
	Non-TOU		TOU		Non-TOU		TOU	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Ownership	7,763	0.725 (0.446)	4,362	0.720 (0.449)	7,522	0.725 (0.447)	4,375	0.721 (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)

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

Table 3C-2 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)

Note:

[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; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Chapter 4: Social versus private benefits of energy efficiency under time-of-use and increasing block pricing

4.1 Introduction

The energy efficiency gap refers to the fact of failing to invest in seemingly cost-effective energy efficiency technologies (Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). The energy efficiency gap is closely related to underinvestment in energy efficiency by consumers and the private investment in energy efficiency is lower than the socially optimal level. Otherwise, there will be overinvestment in energy efficiency. Motivated by the concern of underinvestment in energy efficiency, many policies and energy efficiency programs are implemented to encourage the adoption of energy efficiency in households. 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 sub-optimal investment decisions, and effective policies can promote energy efficiency and increase investment level.

This study focuses on the impact of rate structures on energy savings from energy efficiency, besides the impacts of other market failures that also influence energy savings and energy efficiency. It is possible that consumers already have an incentive to over-invest in energy efficiency (or private benefits larger than social benefits) under their current rate structures. Novan and Smith (2018) reported that there is over-investment for increasing block rate (IBR) consumers in California (without considering other market failures). 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 counterargument to the efficiency policies.

Energy rate structures have an impact on investments in energy efficiency because different energy bill savings are achieved with different prices (Malatji et al., 2013). Besides, electricity consumption behaviors are also different under different marginal prices (Qiu et al., 2018; Faruqui and Sergici, 2010). Currently, electricity prices are regulated and are usually charged higher than their marginal costs. These regulated prices thus distort incentives for investment in energy efficiency (i.e., 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 estimation of the benefits of energy efficiency and also to help policymakers with the design of incentives for energy efficiency.

Time-of-use (TOU) rate is the most common dynamic pricing plan, which follows the cost of electricity supply more closely (Aigner et al., 1994) and helps smooth the electric load profile, and therefore it is often applied in the demand response programs (Torriti, 2012; Vardakas, et al., 2015). TOU has higher marginal prices during peak hours and lower prices during off-peak hours (Newsham and Bowker, 2010). TOU has already been widely implemented in the United States 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 plans) may lead to different amounts of energy saved from a given energy efficiency measure, and this study will provide empirical evidence of such differences resulting from different plans.

Additionally, it is also possible that consumers' price elasticity 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 changes 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 essay 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 (2019) and others, social benefits include the following components: the avoided electricity generation costs, reduced negative externality costs, deferred investments in capacity, and reduced transmission/distribution costs. Specifically, the research questions for this essay 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 and social savings by decreasing electricity generation and pollution emission for TOU and non-TOU consumers, respectively?

4.2 Literature review

This essay 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 essay will contribute to this strand of literature by evaluating the electricity 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, 2019), but using smart-meter electricity data[6] makes it possible to study more complex consumption behaviors (Burlig et al., 2018). The intra-day timing of

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

electricity savings should be considered, which leads to better estimates of savings compared to those based on 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). The study contributes to this emerging strand of the studies by using high-frequency data and study the hour-by-day savings.

Third, abundant studies have estimated the price elasticities. 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; Filippini, 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 that they reported vary. Different methods have been adopted, such as cointegration regression, the error-correction model, and Computable General Equilibrium (Hughes et al., 2006; Lijesen, 2007; He et al., 2017). 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 essay will provide an estimation of the short-run price elasticity when energy efficiency exists.

I estimate electricity savings in kWh by hour-of-day for consumers enrolled on two plans separately: (1) TOU consumers with and without energy-efficient ACs; (2) IBR or non-TOU consumers with and without energy-efficient ACs. This essay includes both groups of consumers while paying special attention to group (1) since no existing research has specifically examined TOU consumers. The comparison of the two groups helps us explore how electricity savings profiles (savings by hour-of-day) differ under different electricity rates. I 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 only with aggregated consumption rather than a price varying intra-day.

4.3 Theoretical framework, data, and empirical strategy

4.3.1 Theoretical framework

Figure 4-1 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 consumers on different pricing plans.

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[7], the larger the demand for energy efficiency, which can be seen as a "product" to reduce energy consumption.

Figure panels (c) illustrate 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, I 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, I 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 indicates the discrepancy between the private and the socially optimal levels. If private savings are larger than

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

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.

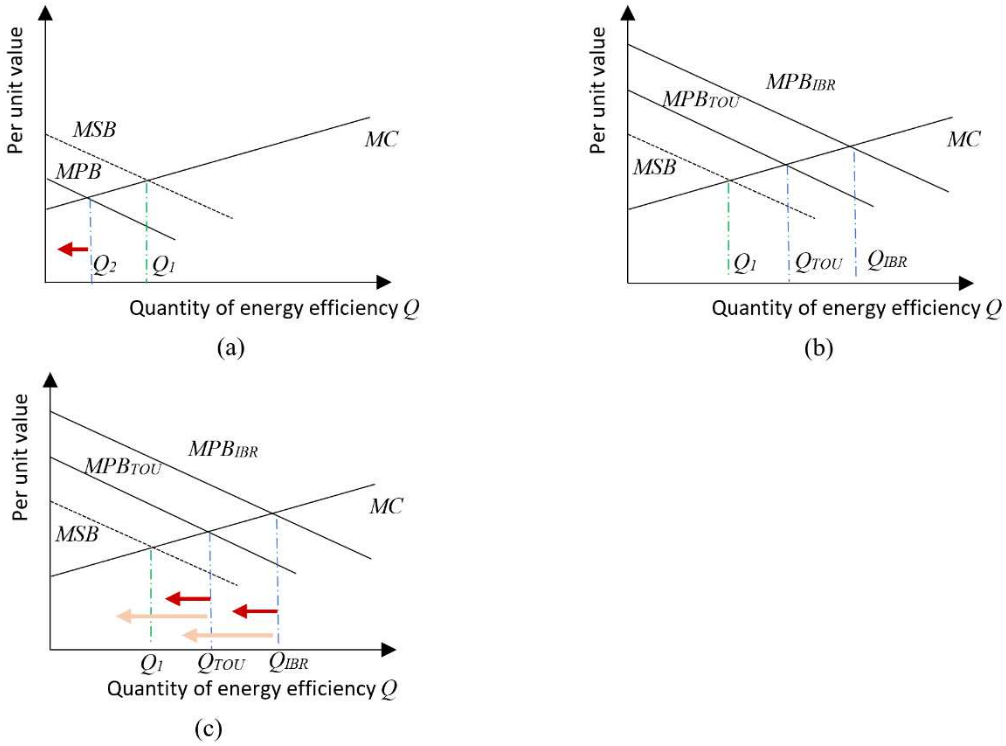

Figure 4-1 Theoretical framework
Note:
MSB stands for marginal social benefit; *MPB* stands for marginal private benefit; *MC* is the marginal cost for adopting energy efficiency; the red arrows indicate the influence of other market failures, such as information asymmetry, split-incentive problem, and inattention.

4.3.2 Data

The data come from the utility of the Salt River Project (SRP) in the Phoenix metropolitan area in Arizona. I focus on energy-efficient AC replacements in this essay. 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, 2019).

I have complied three datasets: two on energy-efficient AC replacements and one smart-metering data. The two separate datasets with energy-efficient AC replacements include (1) the energy-efficient 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 contain 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 three years[8]. In addition, the "Cool Cash" rebate program provides financial incentives [9] and the financial incentives for energy-efficient ACs vary between \$200 to \$800[10]. I 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, I combine the AC replacements recorded by the rebate program with the RET survey because this provides a larger sample for analysis. The final sample compiles the data from about 16,000 households. Altogether, I observe 1,246 households with AC replacements, among which 82 (6.6%) are from the rebate program while 1,164 (93.4%) households are from the self-reported RET survey. Table 4A-1 in the Appendix shows the

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

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

[10] 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 $SEER$ >=18, the incentive is \$800. See more details in http://www.savewithsrp.com/RD/CoolCash.aspx

distribution of dates of replacements. Table 4A-2 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 is 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 Figure 4-2. Given that the exact timing of replacements was not reported in the RET survey, I removed the electricity consumption data before their survey submission dates and only included those after the submission dates, namely, only the "post-treatment" observations. I also dropped 30 days prior to the known replacement dates to avoid abnormal electricity usage during the implementation period. The accounts with multiple zip codes are not included to ensure that changes in electricity consumption are not caused by relocation.

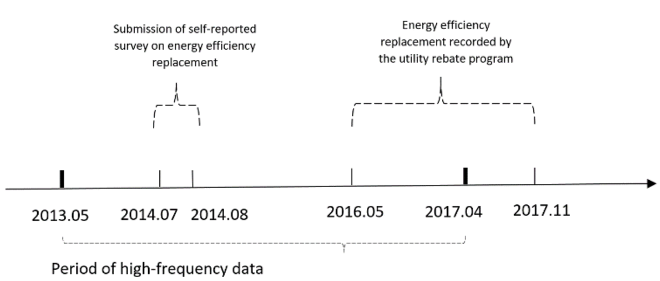


Figure 4-2 Timeline of smart metering data and energy-efficient AC replacements

SRP consumers are enrolled in one of the five different electricity rate plans[11], named E-21, E-22, E-23, E-25, and E-26 (Figure 4-3). E-23 is an IBR rate with time-invariant marginal prices that do not differ by hour-of-day. The other four plans are TOU rates with different on-peak hours and marginal prices. Table 4A-3 gives the detailed per kWh charges for these plans. In this paper, I 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.

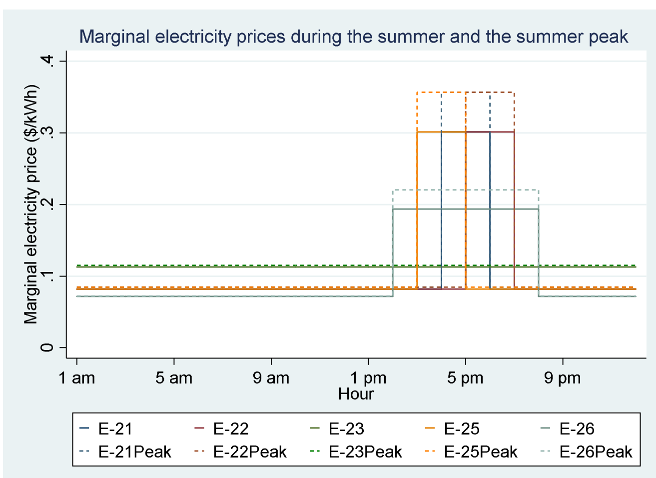


Figure 4-3 The TOU and non-TOU residential electricity pricing plans
Note:
E-21, E-22, E-25, and E-26 are TOU plans, and E-23 is a non-TOU plan; E-21Peak, E-22Peak, E-25Peak, and E-26Peak are the rates in summer peak- July and August.

4.3.3 Descriptive statistics

Figure 4-4 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

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

higher than that of the non-TOU consumers. Usually, electricity 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 one hour later than the non-TOU consumers. The largest demand occurs at 7 p.m. for TOU consumers while occurs 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 4-4 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 their counterparts. Table 4-1 presents the summary statistics of building attributes and housing characteristics.

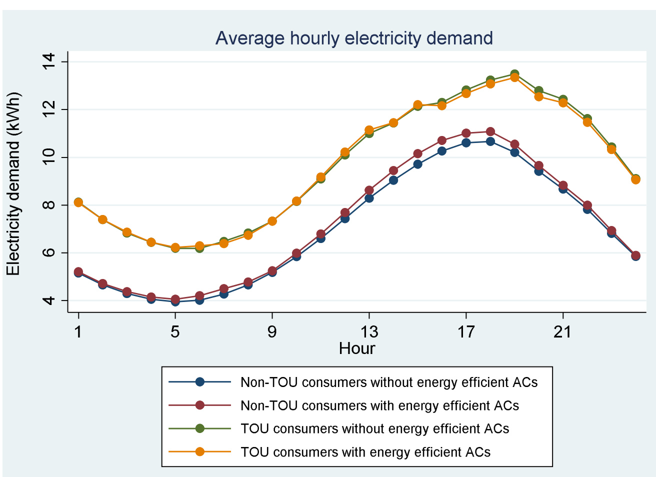


Figure 4-4 Electricity demand in kWh by hour-of-day for TOU and non-TOU consumers

Table 4-1 Descriptive statistics for the TOU and non-TOU consumers with and without energy-efficient ACs

Variable	Obs.	Mean	Std. Dev.	Min	Max

TOU consumers without energy-efficient ACs					
Ownership (renter=0)	4,394	0.72	0.45	0	1
Household income ($1,000)	4,394	61.10	45.05	0	150
Square footage (1,000 ft^2)	4,294	1.87	0.79	0.75	3
Household size	4,283	2.42	1.23	1.5	5
White	4,151	0.75	0.44	0	1
Stories	4,185	1.27	0.49	1	3
Vintage	4,394	26.88	17.92	0	65
Age of household head	4,165	53.92	15.95	21	75
Primary (seasonal residence=0)	4,322	0.98	0.15	0	1
Swimming pool	4,378	0.40	0.49	0	1
Programmable thermostats	4,394	0.65	0.48	0	1
Dwelling					
Mobile home	4,230	0.01	0.10	0	1
Single-family house	4,230	0.82	0.38	0	1
TOU consumers with energy-efficient ACs					
Ownership (renter=0)	496	0.84	0.37	0	1
Household income ($1,000)	496	69.24	45.11	0	150
Square footage (1,000 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)	7,824	0.72	0.45	0	1
Household income ($1,000)	7,824	45.03	40.70	0	150
Square footage (1,000 ft^2)	7,381	1.51	0.79	0.75	3
Household size	7,422	2.07	1.06	1.5	5
White	7,319	0.75	0.43	0	1
Stories	7,167	1.17	0.42	1	3
Vintage	7,824	29.98	19.78	0	65
Age of household head	7,143	60.38	14.73	21	75
Primary residence (seasonal residence=0)	7,510	0.90	0.30	0	1
Swimming pool	7,739	0.16	0.36	0	1
Programmable thermostats	7,824	0.52	0.50	0	1
Dwelling					
Mobile home	7,354	0.05	0.21	0	1
Single-family house	7,354	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 ($1,000)	731	55.84	44.08	0	150
Square footage (1,000 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

4.3.4 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 the TOU plans is not mandatory (Qiu et al., 2017) and there is endogeneity. Consumers can switch between rate plans during billing cycles. To help address this endogeneity, I attempt to apply fixed effects to control for any confounding factors, such as housing characteristics and socio-demographics that could simultaneously influence enrollment in the 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 consumers separately so that I can compare consumers on different plans. I dropped the households that switched between TOU and non-TOU plans (9.3% of consumers) and focus only on households who stayed on the same rate plan.

I conduct propensity score matching to eliminate any systematic differences between consumers with and without energy-efficient ACs. Among various algorithms, I use the algorithms with the smallest median bias, that is, the radius matching with the caliper of 0.01[12]. For a customer with an energy-efficient AC, I find a control customer with similar housing attributes and demographics but without an energy-efficient AC. Then, I conduct the fixed effects regression on these matched consumers. Only the households that are matched (or on the common support) are used for the statistical analysis (Figure 4A-1 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 4A-4) shows that the covariates for the treated and control groups are comparable to each other after propensity score matching. Solar panel installation is not included as the covariates because the data suggests that its adoption is comparatively independent of the decision to adopt energy efficiency[13].

[12] 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 building with a treated building.
[13] The correlation between AC replacements and solar panel installation is -0.0685, which suggests its impact on AC replacements is very weak.

I 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.

4.4 Econometric analysis and results

4.4.1 Electricity savings by hour-of-day

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

$$Demand_{ihd} = \alpha_i + \sum_{h=1}^{24} \beta_1^h EE\_AC_{id} * hour\_of\_day_h + \beta_2 Price_{ihd} + \beta_3 CDD_{ihd} + \beta_4 HDD_{ihd} + \beta_5 Holiday_d + \beta_6 Weekday_d + \tau_y + \delta_m + \gamma_h + \varepsilon_{ihd} \quad (4\text{-}1),$$

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 I am 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 that this essay is 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[14]. α_i is the

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

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. I include all the energy-efficient AC consumers in this main analysis: those recorded by the utility rebate program and also the self-reported ones.

Figure 4-5 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). I 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 the late afternoon and evening for all the consumers, which are usually the peak hours. This is intuitive since the savings are larger when electricity consumption is also larger during these peak hours. The full regression results are listed in Table 4A-5. Coarsened exact matching is also conducted (Appendix 4B) as a robustness check, which gets results generally consistent with those using propensity score matching[15].

[15] I 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 changes or environmental campaigns 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.

There are two possible reasons why TOU consumers yield different savings than non-TOU consumers[16]. Firstly, the TOU consumers have higher consumption than IBR consumers (Figure 4-4), and the high-usage consumers are usually those with higher incomes[17]. The lower-income households on the non-TOU plan may have less efficient electric appliances (Cayla et al., 2011), and comparatively, they 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 they experience greater behavioral changes, such as rebound effects. Their ACs may be set to lower temperatures after retrofits, which leads to fewer 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 prices for the IBR consumers is positive, which is caused by the fact that the marginal electricity price increases as consumers increase their electricity consumption.

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

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

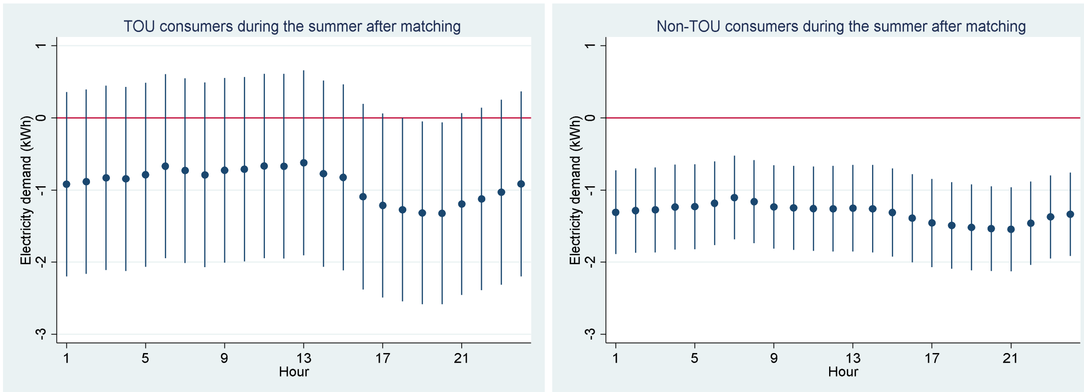


Figure 4-5 Estimates of electricity savings by hour-of-day for TOU and non-TOU consumers

Note:

Propensity score matching is applied before the fixed effects regression. Each plot has 24 coefficients with 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 prices, CDD, HDD, holiday, and weekend are included as covariates.

4.4.2 Overlap of peak hours with electricity savings

Figure 4-6 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, which are taken from the regressions in the former section but formatted as positive values. The figure reveals that a correlation exists between the hours of saving and the prices 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 the estimation of money saved on bills because calculation using average prices and average reduction in consumption ignores a “timing premium” (Boomhower and Davis, 2019). Furthermore, intra-day timing also matters for estimating environmental pollutants during electricity generation, which also varies throughout the day (Sherwin and Azevedo, 2020).

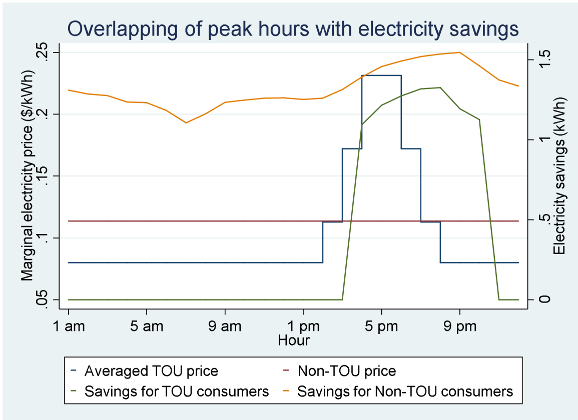


Figure 4-6 Overlap of electricity savings by hour-of-day and marginal electricity prices[18]
Note:
The non-TOU price is the increasing block rate (E-23) while the weighted-average electricity price for TOU consumers is the average of all the TOU prices.

4.4.3 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. I run the regression in equation (4-1) individually for each treated household. Figure 4-7 shows the coefficients from these regressions. 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

[18] In Figure 4-6, 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, I treat these savings in these hours as zero.

the savings are very heterogeneous among households, and it is possible that some households have no electricity savings at all after AC replacements.

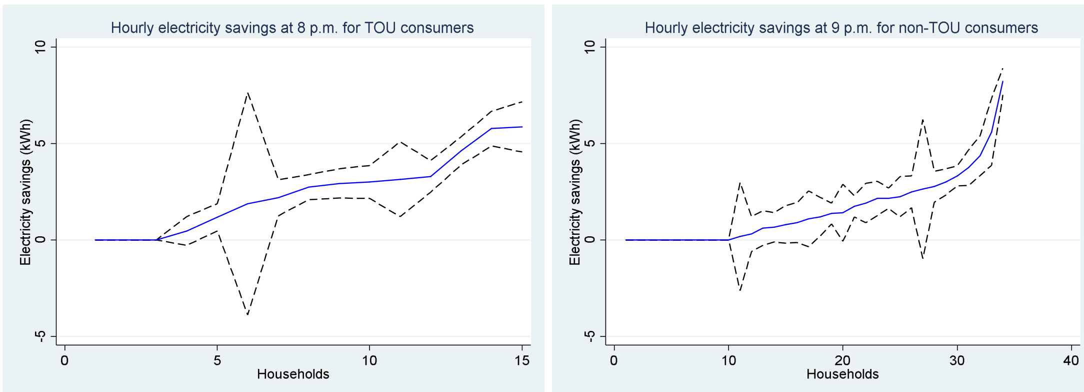


Figure 4-7 Heterogeneity in hourly electricity savings among households[19]
Note:
The dashed black lines show the 95% confidence intervals. All regressions are estimated with household fixed effects and time fixed effects included. Electricity prices, CDD, HDD, holiday, and weekend are also included as covariates.

4.4.4 Price elasticity

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

[19] 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).

$$Demand_{ihd} = \alpha_i + \beta_1 Price_{ihd} + \beta_2 Price_{ihd} * EE\_AC_{id} + \beta_3 CDD_{ihd} + \beta_4 HDD_{ihd} + \beta_5 Holiday_d + \beta_6 Weekday_d + \tau_y + \delta_m + \gamma_h + \varepsilon_{ihd} \quad (4\text{-}2),$$

where β_1 implies the average changes in quantity demanded when prices change without energy efficiency; β_2 is the coefficient on the interaction terms of electricity prices and energy-efficient ACs and it tests whether the average price elasticities differ for consumers with the presence of energy efficiency[20]. 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 4-2) 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. Price elasticity is calculated to be -0.13 without energy efficiency, according to the definition formula of price elasticity[21]. 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

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

[21] 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.

electricity demand. Policy implications regarding this change in price elasticities are made in the section of policy implications.

Table 4-2 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

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

4.4.5 Robustness check

In this section, counterfactuals are created using a machine learning approach. Machine learning is more flexible in terms of model specification and it does not assume 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. I use the pre-treatment data to train the model and use the trained model to predict the counterfactual for each household.

Following (Burlig et al., 2018), I apply the Least Absolute Shrinkage and Selection Operator (LASSO) method[22]. 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 dates are used as pre-treatment data. The predictors include all possible building attributes and socio-demographics. After the counterfactuals are created, I use a difference-in-difference strategy to get the average treatment effect. The formula is as follows:

$$\hat{\beta} = \left(y_{T,post} - \hat{y}_{T,post}\right) - \left(y_{T,pre} - \hat{y}_{T,pre}\right) - \left(y_{C,post} - \hat{y}_{C,post}\right) - \left(y_{C,pre} - \hat{y}_{C,pre}\right) \quad (4\text{-}3),$$

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[23] (Figure 4-8) show that the pattern of electricity savings is similar to the main results, but the magnitude of the estimates seems to be larger. The largest electricity savings also occur during peak hours. The variation between the largest and

[22] 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.
[23] The self-reported replacements are excluded since clear installation dates are not available for them.

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 tends to attribute some of the variations to household fixed effects.

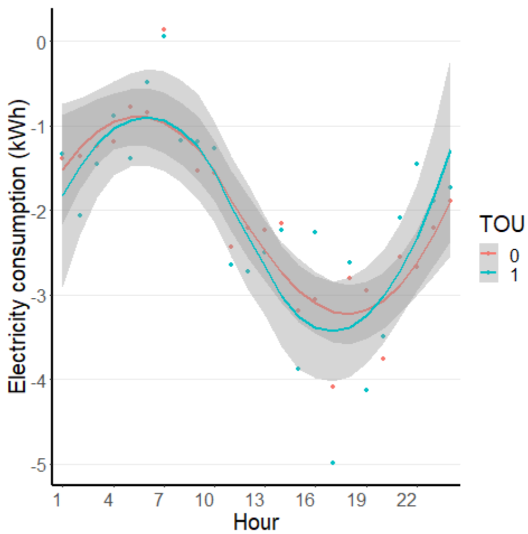


Figure 4-8 Estimates of electricity savings by hour-of-day during the summer months
Note:
The blue line is for the TOU consumers, and the red line is for the non-TOU consumers. The grey area is the 95% confidence interval with the standard error[24].

4.5 Private and social savings

4.5.1 Comparison of private *vs.* social savings

I 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

[24] The method for computing standard errors after model selection methods is not yet well addressed. Thus following (Prest, 2018), I use an OLS regression.

electricity savings. The total private savings are obtained by summing up the daily savings across all summer days[25].

The social savings are calculated by incorporating the reduction in environmental damages from pollutants. I 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). I 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[26]. The system lambda is the system marginal cost[27], which is usually calculated to minimize production costs among different production resources. I 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

[25] 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 $5,000. The details are seen in Table X6 in Appendix A.
[26] https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data
[27] https://www.e-education.psu.edu/eme801/node/532

following (Novan and Smith, 2018). I also included the deferments in transmission/distribution investments. According to eia.gov[28], the average electricity delivery cost is estimated to be 3.2 cents/kWh (in 2016), including the costs of transmission infrastructure, distribution equipment, labor costs, and others. The avoided transmission and distribution costs are calculated by multiplying the average delivery cost by the total decreased consumption.

The TOU consumers with energy efficiency save $263 on electricity bills (Table 4-3) 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, 2019), 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

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

electricity using behaviors. The TOU plan has a 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 this study.

Table 4-3 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 benefits ($)	29.0	124.5
Generation savings ($)	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%

I also tried an alternative set of the marginal damage factors, following (Azevedo et al., 2017)[29]. Compared to the previous set of factors, the alternative factors are larger for CO_2, NO_X, and particulate matter while smaller for SO_2. This alternative factor set also has separated different seasons and I use the factors for the summer season. The results (Table 4-4) 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 savings by 32%. Again, the TOU plan yields a slightly larger deviation between private and social savings in comparison to the non-TOU plan.

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

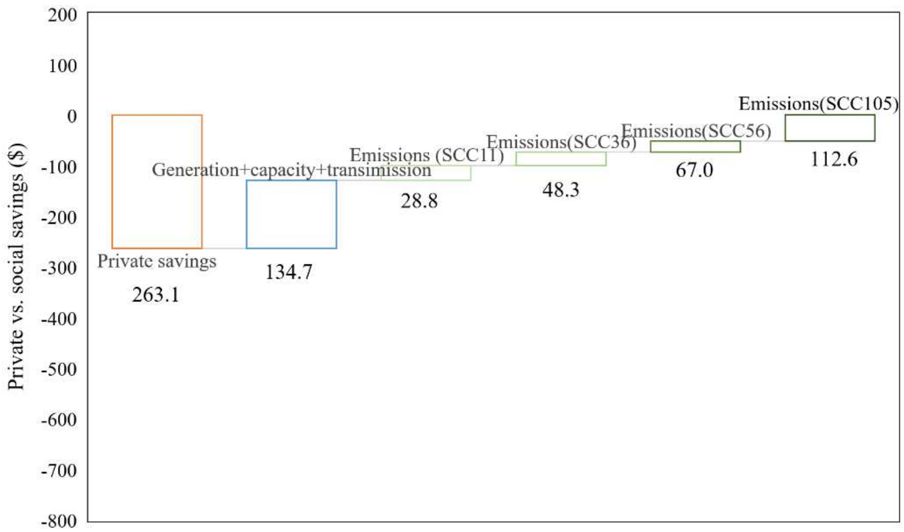
Table 4-4 Average electricity savings from energy-efficient AC using alternative marginal factors

	TOU consumers	Non-TOU consumers
Private savings ($)	**263.1**	**695.4**
Social savings ($)	**182.1**	**527.3**
Environmental benefits ($)	47.4	174.8
Generation savings ($)	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%

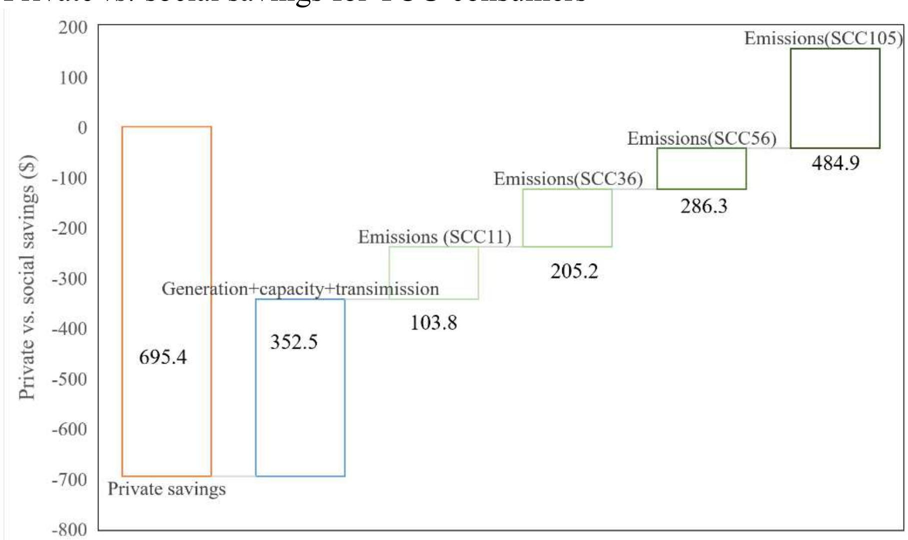
4.5.2 Scenario analysis

The social cost of carbon (SCC) is assumed to be at $35 for a metric ton of carbon dioxide in the last section. However, there is large uncertainty for the long-term damages from carbon dioxide (Tol, 2005). Considering this uncertainty, I 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 (Figure 4-9). Therefore, my 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.



Private *vs.* social savings for TOU consumers



Private *vs.* social savings for non-TOU consumers

Figure 4-9 The comparison of private *vs.* social savings under different scenarios
Note:
The savings on the vertical axis is formatted negative for ease of comparison. If the sum of all bars is zero, the social savings are equal to the private savings.

4.5.3 Discussion

Investments in energy efficiency are voluntary for consumers. Although this essay matches the households on many key observable characteristics (socio-demographics and housing characteristics), some heterogeneity remains with some 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, I provide additional evidence that the potential time-variant individual-specific unobservables do not pose a big threat to my estimates. I 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 replacements. This indicates that the parallel trend assumption is satisfied (Figure 4A-2). After treatment, the results are generally consistent with the main analysis. Based on the analysis, the non-TOU consumers have reduced electricity consumption after the replacements; however, the TOU consumers do not seem to have reduced electricity consumption. This may be due to the possibility that savings only occur during specific hours for TOU consumers and average hourly savings are not detected in this analysis (Figure 4-5).

This essay 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 Figure 4-1(b). The existence of additional market failures could further 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 the conclusion of over-investment will not hold.

The finding that consumers have an incentive to overinvest under TOU and IBR rates does not contradict with the findings in Essay 1, which shows that empirically, residential consumers have a pay-back period as long as 30 years (Table 2-5), implying under-investment in energy efficiency. As stated earlier, the effects of other market failures are not considered in Essay 3, and this essay only focuses on the impacts of rate structures conditional on the existence of other market failures. There could still be net underinvestment and long payback periods when other market failures are considered, as is the case in Essay 1.

As indicated in Section 4.3.2, I was not able to gather complete data for all the households. 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 the main analysis comes mainly from the comparison between the treated and the control groups.

4.6 Conclusion and policy implications

This essay provides an empirical assessment of the effects of two different pricing plans on electricity savings from energy-efficient AC replacements for residential buildings (conditional on the existence of other market failures). Using a rich dataset of hourly electricity consumption of about 16,000 consumers from 2013-2017 in Arizona, I estimate the hour-of-day electricity savings and then use the estimated hourly savings to estimate their private and social benefits. The results show that for TOU consumers, the private savings are greater than the social savings, while for non-TOU consumers, the private savings also exceed the social savings, but by a lower percentage. In addition, I find that energy efficiency makes the electricity demand more elastic to price changes, suggesting energy technologies help the consumers better respond to price changes.

The results have important policy implications. First, to address the market failures 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, causing either over-investment or under-investment in energy efficiency. The results show that the private benefits of non-TOU consumers exceed the social benefits to a lesser extent (when other market failures are not considered). This indicates non-TOU consumers are more likely to underinvest in energy efficiency than TOU consumers. Therefore, one policy implication is that energy efficiency should target consumers on the non-TOU plan than those on the TOU plan. Larger incentives should be provided to non-TOU consumers who are less likely to over-invest in energy efficiency.

Second, this essay finds that energy efficiency makes consumers more elastic, indicating that energy efficiency could help the utility companies ease their burden in terms of balancing the load and generation. Since 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 could help to better reduce the peak load.

The results show that price elasticity changes with the presence of energy efficiency. This finding highlights the importance of empirical estimates of the savings from energy efficiency. It is also of significance for the future exploration of changes in revenues of utilities 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.

4.7 Appendices

Appendix 4A: Tables and Figures

Table 4A-1 Years of adoption for energy-efficient AC replacements

Year	Freq.	Percent
Before or in 2014 [a]	1,164	89.88
2016	61	4.71
2017	70	5.41
Total	1,295	100

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

Table 4A-2 Technical attributes of energy-efficient AC replacements recorded by the rebate program

Variable	Obs	Mean	Std. Dev.	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

Note:
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 4A-3 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 Off-peak	\$0.3013 \$0.0820	\$0.3568 \$0.0844	On-peak hours year-round consist of those hours from 3 p.m. to 6 p.m.; All other hours are off-peak.
E-22		On-peak	\$0.3013	\$0.3568	

	Experimental plan for residential super peak time-of-use service	Off-peak	$0.0820	$0.0844	On-peak hours year-round consist of those hours from 4 p.m. to 7 p.m.; All other hours are off-peak.
E-23	Standard price plan for residential service (non-TOU)	≤ 700 kWh 701-2,000 kWh All Additional kWh	$0.1082 $0.1101 $0.1206	$0.1148 $0.1160 $0.1311	--
E-25	Experimental plan for residential super peak time-of-use service	On-peak Off-peak	$0.3013 $0.0820	$0.3568 $0.0844	On-peak hours year-round consist of those hours from 2 p.m. to 5 p.m.; All other hours are off-peak.
E-26	Standard price plan for residential time-of-use service	On-peak Off-peak	$0.1937 $0.0718	$0.2206 $0.0721	Summer on-peak hours consist of those hours from 1 p.m. to 8 p.m.

Note:
This table is similar to Table 3-1, which also shows details of electricity prices, except that the winter season is not included here.

Table 4A-4 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)	4,394	0.72 (0.45)	496	0.84 (0.37)	3,660	0.84 (0.37)	425	0.83 (0.37)
Household income ($1,000)	4,394	61.10 (45.05)	496	69.24 (45.11)	3,660	70.63 (45.31)	425	70.14 (43.34)
Square footage (1,000 ft^2)	4,294	1.87 (0.79)	488	1.96 (0.74)	3,660	1.98 (0.74)	425	1.98 (0.73)
Household size	4,283	2.42 (1.23)	482	2.39 (1.20)	3,660	2.43 (1.24)	425	2.44 (1.22)
White	4,151	0.75 (0.44)	478	0.82 (0.39)	3,660	0.82 (0.39)	425	0.82 (0.39)
Stories	4,185	1.27 (0.49)	492	1.26 (0.45)	3,660	1.26 (0.48)	425	1.26 (0.45)
Vintage	4,394	26.88 (17.92)	496	27.78 (15.99)	3,660	28.47 (16.80)	425	28.12 (15.78)

Household head age	4,165	53.92	471	55.21	3,660	55.11	425	54.78
		(15.95)		(13.87)		(15.04)		(13.78)
Primary residence	4,322	0.98	495	0.98	3,660	0.98	425	0.98
(seasonal residence=0)		(0.15)		(0.15)		(0.13)		(0.13)
Swimming pool	4,378	0.40	496	0.45	3,660	0.46	425	0.46
		(0.49)		(0.50)		(0.50)		(0.50)
Programmable	4,394	0.65	496	0.80	3,660	0.79	425	0.80
thermostats		(0.48)		(0.40)		(0.41)		(0.40)
Single-family house	4,230	0.82	491	0.90	3,660	0.90	425	0.89
		(0.38)		(0.31)		(0.30)		(0.31)
Non-TOU consumers								
Ownership (renter=0)	5,823	0.71	631	0.79	5,745	0.78	600	0.78
		(0.45)		(0.41)		(0.41)		(0.41)
Household income	5,823	51.52	631	59.89	5,745	56.21	600	56.33
($1,000)		(40.39)		(43.61)		(41.35)		(41.32)
Square footage (1,000								
ft^2)	5,823	1.51	631	1.63	5,745	1.60	600	1.61
Household size		(0.79)		(0.78)		(0.79)		(0.78)
	5,823	2.09	631	2.15	5,745	2.12	600	2.14
		(1.06)		(1.08)		(1.09)		(1.08)
White	5,823	0.77	631	0.82	5,745	0.81	600	0.81
		(0.42)		(0.39)		(0.40)		(0.39)
Stories	5,823	1.18	631	1.12	5,745	1.13	600	1.13
		(0.43)		(0.35)		(0.35)		(0.35)
Vintage	5,823	30.36	631	29.77	5,745	30.43	600	30.28
		(19.28)		(17.02)		(18.77)		(17.09)
Household head age	5,823	59.14	631	58.75	5,745	59.30	600	59.10
		(15.16)		(14.44)		(14.59)		(14.48)
Primary residence	5,823	0.90	631	0.91	5,745	0.90	600	0.91
(seasonal residence=0)		(0.29)		(0.29)		(0.30)		(0.29)
Swimming pool	5,823	0.16	631	0.19	5,745	0.19	600	0.18
		(0.37)		(0.40)		(0.39)		(0.38)
Programmable	5,823	0.52	631	0.71	5,745	0.70	600	0.70
thermostats		(0.50)		(0.45)		(0.46)		(0.46)
Single-family house	5,823	0.74	631	0.82	5,745	0.82	600	0.82
		(0.44)		(0.38)		(0.39)		(0.39)

Table 4A-5 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)
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

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

Table 4A-6 Cost-effectiveness of energy-efficient ACs

	TOU consumers	Non-TOU consumers
Annual dollar savings ($)	411.1	1,093.3
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%

Note:
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.

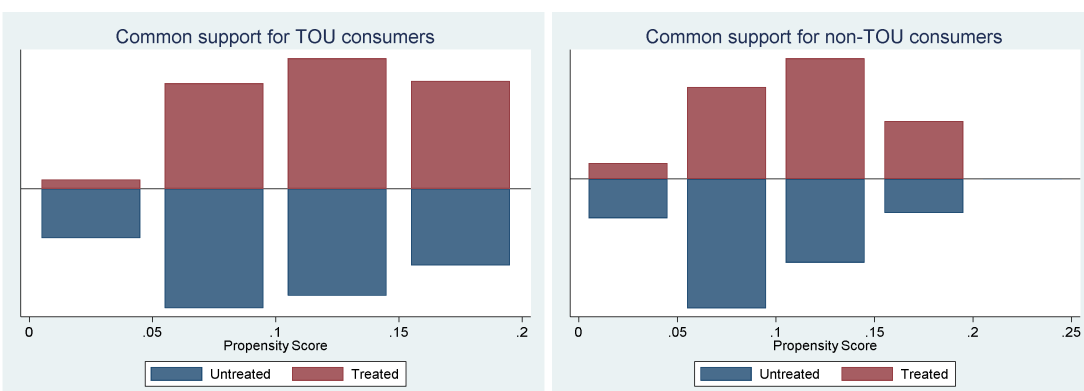


Figure 4A-1 Common support of propensity score matching for the TOU and non-TOU consumers

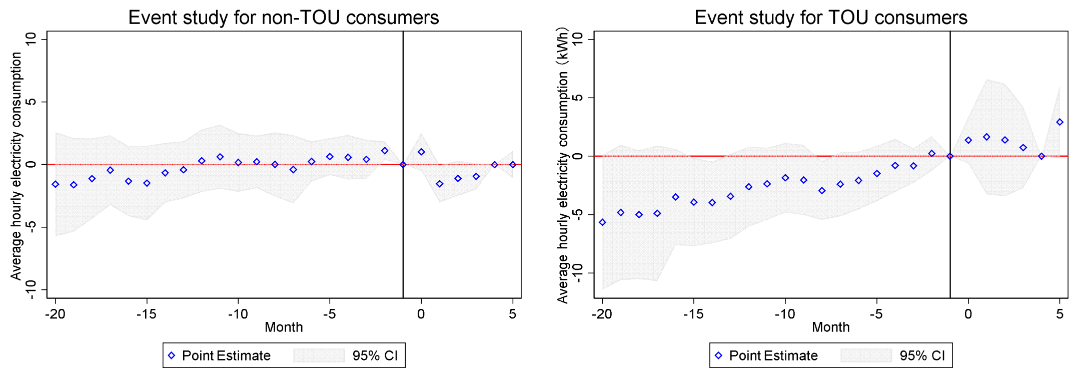


Figure 4A-2 Test of the parallel trend assumption
Note:
This plot includes the estimated coefficients and 95% confidence intervals. Time is normalized relative to the energy efficiency adoption month. Observations before t=-20 are dropped. Price, CDD, and HDD are included as covariates. The regression includes household fixed effects and year fixed effects. Standard errors are clustered at the household level.

Appendix 4B: Coarsened exact matching

I 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 4B-1, which indicates that the covariates are balanced between the control and treated groups after matching.

Table 4B-1 Mean of variables before and after coarsened exact matching for TOU and non-TOU consumers (treatment: energy-efficient AC replacement)

	Before matching				After matching			
Variable	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)	2,202	0.72	496	0.84	930	0.87	382	0.87
		(0.45)		(0.37)		(0.33)		(0.33)
Household income ($1,000)	2,202	0.51	496	0.64	930	0.67	382	0.67
		(0.50)		(0.48)		(0.47)		(0.47)
	2,202	0.71	496	0.75	930	0.78	382	0.78

Square footage (1,000 ft^2)		(0.46)		(0.43)		(0.41)		(0.41)
Household size	2,202	1.00	496	1.00	930	1.00	382	1.00
		(0.00)		(0.00)		(0.00)		(0.00)
White	2,075	0.75	478	0.82	921	0.86	376	0.86
		(0.43)		(0.39)		(0.35)		(0.35)
Stories	2,202	0.29	496	0.26	930	0.23	382	0.23
		(0.46)		(0.44)		(0.42)		(0.42)
Vintage	2,202	0.45	496	0.42	930	0.39	382	0.39
		(0.50)		(0.49)		(0.49)		(0.49)
Household head age	2,094	53.92 (16.06)	471	55.21 (13.87)	914	55.53 (13.52)	372	55.53 (13.53)
Primary (seasonal residence=0)	2,160	0.98 (0.14)	495	0.98 (0.15)	930	1.00 (0.05)	382	1.00 (0.05)
Swimming pool	2,194	0.41 (0.49)	496	0.45 (0.50)	930	0.47 (0.50)	382	0.47 (0.50)
Programmable thermostats	2,202	0.65 (0.48)	496	0.80 (0.40)	930	0.84 (0.36)	382	0.84 (0.36)
Single-family house	2,120	0.82 (0.38)	491	0.90 (0.31)	930	0.95 (0.22)	382	0.95 (0.22)
Non-TOU consumers								
Ownership (renter=0)	7,824	0.72 (0.45)	731	0.79 (0.40)	537	0.81 (0.39)	266	0.81 (0.39)
Household income ($1,000)	7,824	45.03 (40.70)	731	55.84 (44.08)	537	55.21 (43.61)	266	56.07 (44.13)
Square footage (1,000 ft^2)	7,381	1.51 (0.79)	723	1.62 (0.78)	537	1.64 (0.79)	266	1.64 (0.77)
Household size	7,422	2.07	712	2.15	533	2.11	263	2.13
		(1.06)		(1.08)		(1.10)		(1.07)
White	7,319	0.75	691	0.80	530	0.83	259	0.83
		(0.43)		(0.40)		(0.38)		(0.38)
Stories	7,167	1.17	715	1.12	536	1.09	265	1.09
		(0.42)		(0.35)		(0.29)		(0.31)
Vintage	7,824	29.98	731	30.00	537	30.60	266	30.32
		(19.78)		(17.21)		(18.52)		(17.18)
Primary (seasonal residence=0)	7,143	60.38 (14.73)	707	59.16 (14.34)	526	60.06 (13.67)	257	60.06 (13.68)
Swimming pool	7,510	0.90 (0.30)	724	0.90 (0.30)	537	0.92 (0.26)	266	0.92 (0.26)

Programmable thermostats	7,739	0.16 (0.36)	730	0.18 (0.39)	537	0.17 (0.38)	266	0.17 (0.38)
Single-family house	7,824	0.52 (0.50)	714	0.72 (0.45)	536	0.71 (0.46)	265	0.71 (0.46)

The results (Figure 4B-2) 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.

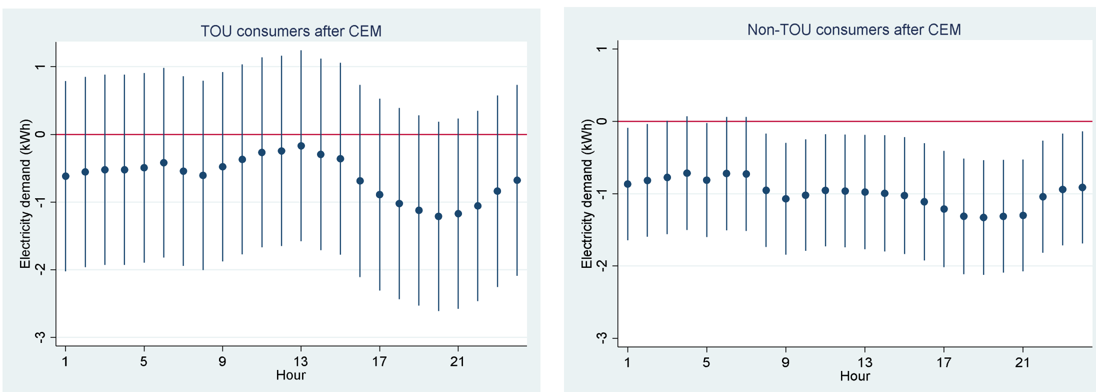


Figure 4B-2 Electricity savings by hour-of-day using coarsened exact matching
Note:
Coarsened exact matching is applied before the fixed effects regression. Each plot has 24 coefficients with 95% confidence intervals. The dependent variable for each regression is hourly electricity demand in kWh. Electricity prices, 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.

Chapter 5 Conclusion

Decreasing electricity consumption through energy efficiency is a key approach to reducing energy production and the associated pollutants and carbon emissions. My dissertation focuses on energy efficiency and energy efficiency gap. This work fills the gap in the existing literature by evaluating the impacts of energy efficiency retrofits, exploring the association between the adoption of energy efficiency and solar panel and electricity rate plans, and examining the social versus private savings from energy efficiency under different rate plans.

Essay 1 evaluates the Energize Phoenix program, including 201 residential buildings and 636 commercial buildings during the period 2008-2013. This essay examines energy savings from this program using fixed effects panel models. The results show the overall energy savings are 12% for commercial buildings and 8% for residential buildings. The realized energy savings are 30-50% lower than those predicted by engineering models. Heterogeneity exists among retrofits for different building types, which should be taken into consideration by building owners and policymakers when it comes to energy efficiency investments or subsidizing these investments. Evidence of the rebound effect for low-income households is also found in Essay 1.

Essay 2 investigates the association between TOU and the adoption of solar panels and energy-efficient air conditioners among residential consumers. The empirical evidence suggests that TOU consumers are associated with a 27% higher likelihood of solar panel installation, but they are not more likely to adopt energy-efficient ACs. A positive correlation between these two adoptions after controlling for other types of confounding factors implies that if policymakers could encourage these two adoptions together, 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.

Essay 3 focuses on the comparison between the private and social savings after energy efficiency replacements under TOU and non-TOU rates. This study applies 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. I attempt to use a combination of matching and fixed effects panel regression to reduce potential endogeneity, which exists because the enrollment in TOU and the adoption of energy-efficient ACs are voluntary for the consumers. The results show that consumers under both TOU and non-TOU rates have an incentive to over-invest in energy efficiency but to different degrees. These results indicate that there should be potentially different levels of policy interventions towards energy efficiency for consumers on different pricing. In addition, energy efficiency would impact the price elasticity of electricity by making the consumers more elastic to price changes.

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