Risk preference and adverse selection for participation in time-of-use electricity pricing programs

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Abstract:

Time-invariant electricity pricing does not reflect daily variation in the cost of producing electricity and thus can cause economic inefficiency. Time-of-use pricing (TOU), which has higher electricity prices during peak hours and lower prices during non-peak hours, is a pricing scheme that can help achieve more efficient levels of electricity consumption. This study examines factors influencing consumers' participation in voluntary TOU programs with particular attention to individual-specific risk and time preferences elicited through multiple price-list experiments. Evidence from a study of 398 homeowners in Arizona and California, U.S., indicates that more risk averse consumers are less likely to enroll in TOU programs. The results suggest evidence of adverse selection, with households who consume less energy during peak hours being more likely to enroll in TOU programs. Time preferences are found to have a statistically significant and negative impact on consumers' adoption of programmable thermostats, a technology that can allow households to better respond to TOU pricing. However, we find no evidence that consumers' decisions to enroll in TOU programs and adopt programmable thermostats are correlated. Our results have important implications for policymakers and utility companies, which attempt to increase participation in voluntary TOU programs.

Key words: Adverse selection; Programmable thermostat; Risk preferences; Time-of-use electricity pricing

Classification codes: D12, C91, L94, Q41

1. Introduction

Time-invariant retail electricity rates cause economic inefficiency when there is intraday variation in the demand for electricity and production costs vary by time of day (Williamson, 1966). If electricity load profiles were flat, then base load generating plants such as coal and nuclear power plants would meet all demand. However, with a rapid increase in the electricity demand in many markets during peak hours, only marginal facilities with greater marginal costs can ramp-up sufficiently fast (e.g., natural gas power plants). These marginal facilities are then employed for generating the supply to meet the increased demand. As a consequence of using a time-invariant pricing structure, there is a welfare loss estimated to be between 5% and 10% of wholesale energy costs (Borenstein & Holland, 2005).

One avenue for reducing this welfare loss is to adjust retail prices intraday based on the marginal cost of electricity provision. In a real time pricing (RTP) scheme, prices vary at high frequency (e.g., hourly) (Allcott, 2011; Wolak, 2011). Although conceptually RTP can reduce welfare losses, there are associated high fixed implementation costs and concerns over whether consumers would indeed exert the time and effort to respond to price changes on an hourly schedule (Wolak, 2011). A related but simpler approach implemented in many markets, is time-of-use pricing (TOU), which is third-degree price discrimination where customers are charged higher prices during peak hours and lower prices during non-peak hours. For utility companies, TOU pricing can help improve their load profile by shifting electricity usage from peak hours to non-peak hours. This improves economic efficiency by aligning prices more closely with marginal costs and reduces or delays capital investment in marginal facilities. Previous studies focusing on the effects of TOU pricing plans on energy consumption patterns (Caves et al., 1984; Faruqui and Sergici, 2010; Newsham and Bowker, 2010; Jessoe et al., 2014) have found that residential TOU

customers generally shift their peak-hour energy consumption to non-peak hours. However, related studies focusing on commercial sectors (Hirschberg and Aigner, 1983; Park and Acton, 1984; Aigner et al., 1994; Jessoe and Rapson, 2014; Faruqui et al., 2014; Qiu et al., 2015) have not reached a consensus on whether commercial customers respond to TOU pricing.

Despite the overall welfare gains and potential for retail (Faruqui and Sergici, 2010) and for commercial (Qiu et al., 2015) customers to reduce their electricity costs under TOU, there are two major issues that can confound the success of TOU: adverse selection and under-participation. Similar to many voluntary programs, there is the concern of adverse selection—i.e., voluntary TOU participants are households who consume relatively less energy during peak hours before switching to TOU pricing (Jessoe and Rapson, 2014). These households can take advantage of lower non-peak energy prices to reduce their energy bills even without changing their energy consumption behavior. Thus, the financial burden (less energy revenue) for a utility company will then be passed onto non-TOU customers. The second issue, under-participation in a potentially cost-reducing program, is similar to the well-known energy “efficiency paradox”—“cost-effective energy-efficient technologies based on simple net present value calculations at current prices enjoy only limited market success” (Brown, 2001; Jaffe and Stavins, 1994). Previous studies have found that behavioral factors (such as bounded rationality and high implied discount rates, Sanstad and Howarth, 1994), market failures (such as principal–agent problems, Jaffe and Stavins, 1994), as well as institutional and organizational factors (such as a trade-off with non-energy specific goals, Weber, 1997) can cause the efficiency paradox.

In this study, we present evidence on the presence of adverse selection and individual-specific factors that influence homeowners’ decisions to enroll in TOU pricing programs. Critically, we move beyond previous studies that only consider sociodemographic of TOU

participants (Baladi et al., 1998) and focus on two potentially critical individual-specific factors affecting enrollment: risk and time preferences. For a household, switching from familiar time-invariant electricity pricing to a novel TOU program under the expectation of reduced electricity bills is a decision that involves risks. Because of the inherent difficulties in projecting and managing future peak vs. non-peak energy usage, there is a risk for a household as to whether expected cost savings will actually be realized. Even if a household expects cost savings from enrollment, a sufficiently risk averse household may optimally choose not to participate. In addition to the element of risk, there is a time dimension that can potentially influence a household's decision to enroll in TOU programs. Households who are more impatient (i.e., who have higher individual-specific discount rates) can be more reluctant to enroll because of potential bill increases during the period of adjusting one's energy usage schedule to the new peak vs. non-peak pricing scheme. On the other hand, households who are more patient may be more willing to risk potentially incurring higher initial bills but with future savings over a longer-term horizon. However, because there is no up-front cost to enroll in TOU programs and for the markets considered in this study participants are not required to sign a long-term contract, it is likely that enrollment decisions are not affected by individual-specific discount rates. In contrast, time preferences could play a role in TOU participation indirectly by affecting a household's willingness to adopt¹ a programmable thermostat². This home technology allows better response to time-variant electricity pricing (Faruqui and Sergici, 2010 and Faruqui et al., 2010) but involves up-front costs that are only potentially offset through a future stream of cost savings. As indicated

¹ In this paper, adopting a programmable thermostat captures two situations: (1) a household installed such technology after purchasing a home; (2) a household purchased a home with such technology already installed.

² While programmable thermostats can facilitate easier management of household peak vs. non-peak energy usage, programmable thermostats are not a requirement for enrolling in TOU. This is in contrast to many direct load control programs where utilities can remotely adjust customer energy usage.

in previous studies that have investigated the adoption of energy-efficient technologies (Hassett and Metcalf, 1993; Erdem et al., 2010; Qiu et al., 2014a), individuals with higher impatience are less likely to adopt.

To develop a better understanding of the influences and barriers to participation in TOU pricing, we proceed in two steps. In the next section, an illustrative model of the household decision in the presence of risk is developed. With this as a foundation, we present evidence from a survey of a representative sample of 398 homeowners in Arizona and California. We choose to analyze these two states because the former serves as a representative state with more conservative energy programs while the latter represents states that are more aggressive in this regard. In addition to background information on home and homeowner characteristics, energy usage, programmable thermostat adoption, and TOU participation, measures of homeowners' risk and time preferences were elicited using popular multiple price-list (MPL) techniques. Evidence from a set of econometric models indicates four key results: (1) risk averse consumers are less likely to enroll in voluntary TOU programs, (2) homeowners with lower peak-energy usage under time-invariant pricing are more likely to enroll (i.e., adverse selection), (3) time preferences influence investments in programmable thermostats but not TOU participation, and (4) there does not appear to be a strong relation between TOU participation and programmable thermostat adoption. Given these findings, we conclude with a discussion of difficulties and opportunities for electric utilities to improve their programs and increase voluntary TOU participation.

2. Illustrative model of TOU participation

To illustrate the consumer decision to voluntarily enroll in a TOU pricing program, the influence of risk on the decision process, and welfare implications and adverse selection problems, we

develop a model from microeconomic principles which will be analyzed empirically in the next section. We begin with a power company practicing a two market (non-peak and peak) price-discriminating scheme; letting E_n and E_p denote a household's non-peak and peak energy usage, respectively. The power company sets per-unit prices r_n and r_p , in the non-peak and peak markets, respectively. Theoretically, with no regulation, the utility would determine these prices by equating marginal revenue to costs in each market as local monopolies. If regulated, they would determine the two market prices with the constraint of being a nonprofit (or some other regulation) that is permitted to price discriminate.

Assume that a household takes these prices as constant and is interested in minimizing expenditures for a given level of utility, u^0 . Utility can be considered some set level of environmental-household comfort. A household attempts to maintain this utility by purchasing energy along with considering a discrete purchase of installed programmable thermostats, T . This possible thermostat purchase is a household technical change that positively influences preferences by providing a more efficient use and allocation of non-peak, E_n , and peak, E_p , energies. Let the initial cost of the technology be r_T with an associated stream of returns (energy savings) discounted by a household's implicit time preference for income, δ . The discounted returns are then $PV(\delta)$, and for an infinite horizon, $PV(\delta) = ES/\delta$, where ES is annual energy savings. It also indirectly affects household utility by reducing any perceived risk in selecting TOU. This assumes that a household has some adverse-risk preferences toward TOU; represented by the risk-averse coefficient ρ , so $\rho(T)$. Household preferences with and without the thermostat technical change may be represented by utility functions $u_T[E_n, E_p, PV(\delta), \rho(T)]$ and $u[E_n, E_p, \rho(T)]$, respectively.

2.1 No thermostat adoption

Initially, assuming no adoption of a programmable thermostat technical change, the household then faces the following problem

$$e(r_n, r_p, u^o) = \min \{r_n^o E_n + r_p^o E_p, \text{ s.t. } u^o = u[E_n, E_p, \rho(T)]\}. \quad (1)$$

The expenditure function $e(r_n, r_p, u^o)$ is defined by (1). In the case of no TOU, the prices are equivalent, $r_n^o = r_p^o$. With TOU, assume r_n declines to r_n' and r_p rises to r_p' , so $r_n' < r_n^o = r_p^o < r_p'$. Solving the household problem yields the Hicksian demands for non-peak and peak usage, $h_n[r_n, r_p, u^o, \rho(T)]$ and $h_p[r_n, r_p, u^o, \rho(T)]$

The household's decision to enroll in a TOU program is a self-selection decision, depending on the household's change in consumer surplus. With a positive consumer surplus change, the household will enroll and with a corresponding negative change, it will not. Assuming risk-neutral preferences, $\rho = 0$, an exact measure of this change in consumer surplus may be derived by considering how much the household would have to be taxed at prices r_n' and r_p' to make it as well-off as it was at prices r_n^o and r_p^o . This amount C , called compensating variation in income, is

$$C = e(r_n', r_p', u^o) - e(r_n^o, r_p^o, u^o). \quad (2)$$

If $C < 0$ (tax), then the household will self-select and enroll in TOU programs. Otherwise, at $C > 0$, the household would have to be paid to be willing to enroll in TOU. Considering each of the price changes separately, the compensating variation, C_n , for a non-peak price decline is

$$C_n = e(r_n', r_p^o, u^o) - e(r_n^o, r_p^o, u^o) < 0,$$

and for a peak price rise is

$$C_p = e(r_n^o, r_p', u^o) - e(r_n^o, r_p^o, u^o) > 0.$$

For small changes in prices, it can be assumed that price effects are independent, so $\partial C_n / \partial r_p = \partial C_p / \partial r_n = 0$. Thus, the two price changes can be summed, $C = C_n + C_p$. Given Hotelling's theorem

$$C = \int_{r_n^o}^{r_n'} h_n(r_n, r_p^o, u^o) dr_n + \int_{r_p^o}^{r_p'} h_p(r_n^o, r_p, u^o) dr_p.$$

If the household's demand for peak energy is higher than non-peak, the area under the Hicksian demand function for peak energy will be larger. This leads to a decline in the likelihood for enrolling in TOU. A household with lower demand for peak energy will then have a greater tendency to select TOU than will a household with a relatively higher demand, which leads to adverse selection.

If $\partial C_p / \partial r_n \neq 0$, then $\partial C_p / \partial r_n = \int_{r_p^o}^{r_p'} \partial h_p / \partial r_n dr_p$. Assuming non-peak and peak energies are net substitutes, then $\partial h_p / \partial r_n > 0$, which implies a decline in non-peak rates will reduce the peak energy surplus. Similarly, if $\partial C_n / \partial r_p \neq 0$, then $\partial C_n / \partial r_p = \int_{r_n^o}^{r_n'} \partial h_n / \partial r_p dr_n$, which implies an increase in peak rates will increase non-peak energy surplus. At some point as the wedge between these prices widens, it may result in all households self-selecting TOU.

2.2 Thermostat adoption

Considering the discrete thermostat purchase; assume that it takes on the values of 0 and 1 depending on if it is adopted or not. Suppress the variables $u[\rho(0)] < u_T[PV(\delta), \rho(1)]$, which means the satisfaction with a programmable thermostat technical change is higher than without. In conjunction with this relation, $\rho(1) < \rho(0)$, which means a programmable thermostat technical change is risk reducing. In terms of implicit time preference, $\partial u_T / \partial \delta = (\partial u_T / \partial PV)(dPV/d\delta) < 0$.

An increase in a household's time preference for money will reduce its satisfaction from purchasing a thermostat.

How much a household is willing to pay for $T = I$ is determined by the thermostat demand function

$$T = \begin{cases} 1 & \text{if } r_T \leq r_T^* \\ 0 & \text{if } r_T > r_T^* \end{cases},$$

where r_T^* denotes a household's threshold price (reservation price) for adopting programmable thermostats. The compensating variation for this purchase, C_T , when $r_T' \leq r_T^* < r_T^o$ is

$$C_T = e_T(r_n', r_p', r_T' u^o) - e(r_n', r_p', u^o) < 0, \quad (3)$$

where $e_T(r_n', r_p', r_T' u^o)$ is the technical-change expenditure function associated with the given level of utility u^o and prices (r_n', r_p', r_T') . The inequality assumes the household will receive a positive surplus from adoption, and it consequently adopts.

Solving for the minimizing no technical-change expenditures at prices (r_n', r_p') and utility u^o , $e(r_n', r_p', u^o)$, in (3), substituting into (2), and rearranging, yields

$$C + C_T = e_T(r_n', r_p', r_T' u^o) - e(r_n^o, r_p^o, u^o).$$

If the price for adopting a programmable thermostat yields a positive surplus, then by purchasing the technology, the household's surplus from enrolling in TOU, C , is augmented by C_T . Selecting TOU with a thermostat adoption will then enhance a household's satisfaction relative to not adopting.

2.3 Risk aversion

Relaxing the assumption of risk neutrality by assuming risk-averse preferences, the household now has a risk premium, which is the extra return to compensate for the risk in selecting TOU. By definition, a risk-averse household will not be indifferent to enrolling in TOU along with adopting the technical change when

$$C + C_T = e_T(r'_n, r'_p, r'_T, u^o) - e(r_n^o, r_p^o, u^o) = 0.$$

This point of indifference is not the threshold for selecting the TOU and thermostat combination, given the household is not compensated for accepting some risk. Formally, the household's threshold for selection is

$$e(r_n^o, r_p^o, u^o) - e_T(r'_n, r'_p, r'_T, u^o) = R[\rho(T)] > 0,$$

where R denotes the risk premium. For self-selection, a risk-averse household not only must be able to reduce its expenditures but it must reduce expenditures to the point where it is paid for having to accept some risk. This risk premium, compensation, is a function of a household's aversion to risk. The more risk aversion, the larger the ρ and the greater the risk premium, and therefore the lower the expenditures must be for TOU and thermostat adoption. However, this risk premium is mitigated by the adoption of the technology, $R[\rho(1)] - R[\rho(0)] < 0$.

Based on the household problem (1) of minimizing electricity expenditures for a given level of comfort, Table 1 lists the hypothesized testable signs. The higher a household's risk coefficient (i.e., greater risk aversion), the less likely it is to enroll in TOU programs, while the risk coefficient does not influence the decision to adopt a programmable thermostat. A higher implied discount rate is associated with a smaller likelihood of adopting a programmable thermostat but it does not influence TOU participation. If a household does not consume much energy during peak hours under a flat electricity rate, it will be more likely to enroll in TOU, which

is the adverse selection problem; while this adverse selection problem should not impact adoption of a programmable thermostat. Empirically testing these hypothesized signs will support the theoretical relations and provide an indication on the magnitudes of their influences on TOU and programmable thermostat adoptions. Interest is in establishing both theoretical and statistical relations of risk preference, discount rates, and adverse selection impacts on TOU enrollment and programmable thermostat adoption.

Table 1. Theoretically developed hypothesized signs

Household Preference	TOU	Programmable Thermostat
Risk (CRRA coefficient) ^a	–	0
Discount rate	0	–
Adverse selection	+	0

^a CRRA denotes constant relative risk aversion.

3. Empirical methods

Based upon Table 1, in this section an empirical analysis of households' decisions to enroll in TOU pricing programs and to adopt programmable thermostats is presented. The dataset is from an online survey of a representative panel of homeowners in Arizona and California conducted by a leading market research firm, Lightspeed Research-GMI. Survey participants were compensated for their time through GMI. The survey was conducted between April 12th and April 16th in 2013. We contacted 1000 homeowners who were 21 years or older and the response rate was about 43%. There were 398 final usable responses after we dropped those participants who did not

answer all of the necessary questions.³ The online survey was created using Qualtrics and included three major sections, which we discuss in turn: a risk preference and a time preference elicitation experiment, and questions related to home energy use.

3.1 Risk preference elicitation

For testing household's risk preference's impact on TOU enrollment and programmable thermostat adoption in Table 1, an approach to elicit risk preferences was designed based on the multiple price-list (MPL) method popularized by Holt and Laury (2002). In this method, a direct measure of the individual's constant relative risk aversion (CRRA) coefficient ρ can be revealed from the CRRA utility function, $U(x)=x^{1-\rho}/(1-\rho)$, where x is the level of wealth. The Holt and Laury (2002) method presents a series of choices between two alternative lotteries. The two lotteries in a choice set differ in their expected payoff and probabilities. Based on individuals' choices of lotteries in each choice set, the CRRA coefficient can be calculated. The associated hypothesized sign is listed in table 1.

The risk elicitation approach employed is similar to the original Holt and Laury (2002) experiment except that it was placed in the context of home energy improvement. The original Holt and Laury experiment asked individuals to choose between lotteries with risky dollar returns without any background context for the decision. Recent studies find that individuals exhibit different risk attitudes in different contexts such as recreational, financial, ethical, insurance, or health-related decisions (MacCrimmon and Wehrung, 1986, 1990; Weber et al., 2002; Barseghyan et al., 2011; Einav et al., 2012; Reynaud and Couture, 2012; Menapace, Colson, and Raffaelli, 2015). To elicit risk preferences in the context of home energy consumption, consumers were

³ The original sample in this study is the same as the one in Qiu et al. (2014a). The final usable sample is different because we further dropped the responses that did not complete the time preference elicitation experiment.

provided the choice between two otherwise equivalent home appliances with different potential lifetime energy cost savings (Qiu et al., 2014a). The risk experiment is described in Table 2.

In Table 2, the household chooses between appliances A or B in each row. Decision situation #1 presents two choices: appliance A with a 10% probability of receiving \$400 in energy cost savings and a 90% probability of receiving \$320 in savings, and appliance B with 10% probability of receiving \$770 in energy cost savings and a 90% probability of receiving only \$20 in savings.⁴ The expected cost savings of appliance A is much larger than that of appliance B in decision situation #1. As one moves down the decision situations, appliance B's expected cost savings become larger relative to appliance A. A risk-neutral household should switch from appliance A to B when the expected cost savings of appliance A are equivalent to appliance B, which occurs at decision situation 5. Risk seeking households should switch to appliance B in decision situations 1-4, while risk-averse households should switch in later decision situations. Depending on the decision situation in which households make the switch, the CRRA coefficient can be calculated. The corresponding CRRA coefficient is listed in the last column of Table 2⁵.

Table 2. The risk preference elicitation experiment (Qiu et al., 2014a)

Most energy efficient appliances have greater potential for energy savings. However, because of uncertainty about energy prices, energy use, and technological performance, how much energy cost

⁴ In the Holt and Laury (2002) style MPL risk experiment, both the payoffs and probabilities of the choices are known. In the real world energy related decisions, it is possible that the probabilities and/or payoffs are not known. In such situation, individuals are shown to exhibit ambiguity aversion – known risks are preferred to unknown risks (Ellsberg, 1961; Moore and Eckel, 2002). Though risk aversion and ambiguity aversion are two distinct features, Segal (1987) finds that under the anticipated utility framework risk aversion and ambiguity aversion are almost identical. Kocher and Trautmann (2013) establish experimental evidence that risk aversion and ambiguity aversion are positively correlated. Thus, the results presented in this paper on the impact of risk aversion on energy related decisions can shed some light on the decisions where probabilities and/or payoffs of energy related choices are unknown (Qiu et al., 2014a).

⁵ The CRRA calculation is obtained in the following way. For example for Row 6, first set the expected utility of choosing A equal to that of choosing B at Row 5: $0.5 \cdot 400^{1-p}/(1-p) + 0.5 \cdot 320^{1-p}/(1-p) = 0.5 \cdot 770^{1-p}/(1-p) + 0.5 \cdot 20^{1-p}/(1-p)$ and solve for p which is 0.14. Then, set the expected utility of choosing A equal to that of choosing B at Row 6: $0.6 \cdot 400^{1-p}/(1-p) + 0.4 \cdot 320^{1-p}/(1-p) = 0.6 \cdot 770^{1-p}/(1-p) + 0.4 \cdot 20^{1-p}/(1-p)$ and solve for p which is 0.41. Then the CRRA intervals for Row 6 is [0.14, 0.41].

savings obtained from an energy efficient appliance is uncertain. Consider yourself in a situation where you must purchase an essential home electric appliance. Assume that there are two types of appliance available. *Option A* has more certain energy cost **savings** potential than *Option B*, while *Option B* has a chance to achieve much greater energy cost **savings**. Suppose that these appliances are identical in every other way, except for the difference in total lifetime energy cost **savings**. The lifetime of these two appliances are both 10 years. In each of the 10 decision situations, *Option A* has a total lifetime energy cost **savings** of \$400 with probability P% or \$320 with probability Q% and *Option B* has a total lifetime energy cost **savings** of either \$770 with probability P% or \$20 with probability Q%, where P and Q differs in each decision row. For example, consider decision situation #4. In this situation you have a choice between *Option A* and *Option B*. If you choose *Option A* you have a 40% probability of receiving a total lifetime energy cost **savings** of \$400 and a 60% probability of \$320. If you choose *Option B* you have a 40% probability of receiving a total lifetime energy cost **savings** of \$770 and a 60% probability of \$20. Please make 10 decisions (one for each decision situation) by choosing your 10 most preferred options.

Decision Situation	Option A		Option B		Open CRRA Interval if Subject Switches to Lottery B ²
	Receiving life time energy cost savings ¹		Receiving life time energy cost savings		
1	10% chance of receiving \$400	90% chance of receiving \$320	10% chance of receiving \$770	90% chance of receiving \$20	−∞, -1.71
2	20% chance of receiving \$400	80% chance of receiving \$320	20% chance of receiving \$770	80% chance of receiving \$20	-1.71, -0.95
3	30% chance of receiving \$400	70% chance of receiving \$320	30% chance of receiving \$770	70% chance of receiving \$20	-0.95, -0.49
4	40% chance of receiving \$400	60% chance of receiving \$320	40% chance of receiving \$770	60% chance of receiving \$20	-0.49, -0.15
5	50% chance of receiving \$400	50% chance of receiving \$320	50% chance of receiving \$770	50% chance of receiving \$20	-0.15, 0.14
6	60% chance of receiving \$400	40% chance of receiving \$320	60% chance of receiving \$770	40% chance of receiving \$20	0.14, 0.41
7	70% chance of receiving \$400	30% chance of receiving \$320	70% chance of receiving \$770	30% chance of receiving \$20	0.41, 0.68
8	80% chance of receiving \$400	20% chance of receiving \$320	80% chance of receiving \$770	20% chance of receiving \$20	0.68, 0.97
9	90% chance of receiving \$400	10% chance of receiving \$320	90% chance of receiving \$770	10% chance of receiving \$20	0.97, 1.37
10	100% chance of receiving \$400	0% chance of receiving \$320	100% chance of receiving \$770	0% chance of receiving \$20	1.37, ∞

¹ We use these particular payoff values for the multiple price list risk experiment because they replicate those popularized by Holt and Laury (2002) and have been adopted widely in the literature. For these particular payoff values Option A represents a relatively less variable alternative compared to the risky Option B. This structure leads to the set of 10 gambles with a clean structure where (i) a risk neutral individual should choose Option A four times before switching to Option B (i.e., halfway through the MPL), (ii) a risk averse individual should switch to Option B on one of the gambles 6-10 (depending upon their degree of risk aversion) and (iii) a risk seeking individual should switch to Option B prior to gamble 5 (again, depending upon their degree of risk seeking).

² This column is not shown to the survey participants.

3.2 Time preference elicitation experiment

For testing households' time preference's (discount rate) impact on TOU enrollment and programmable thermostat adoption in Table 1, existing literature has estimated a wide range of implicit discount rates in the context of energy-efficient appliances from 5% to 100% (Hausman, 1979; Dubin and McFadden, 1984; Train, 1985; Sanstad et al., 1995; Verboven, 1999). This motivated eliciting household implied discount rates employing an MPL-style experiment similar to Collier and Williams (1999), Harrison et al. (2002), and Andersen et al. (2008). As in the case of the risk preference MPL, we cast the time preference experiment in the context of energy-efficient home appliances (Table 3).

Similar to Table 2, the household chooses between appliance A or B (both with a lifetime of ten years) in each row in Table 3. Decision situation 1 presents two choices: appliance A with a purchase price of \$1200 and annual energy cost of \$300, and appliance B with a purchase price of \$1600 and annual energy cost of \$280. As a homeowner moves down the decision situations, appliance B's annual energy cost declines. Households who are more patient or have smaller discount rates would switch from appliance A to B in earlier decision situations. Depending on the decision situation in which the household switches, the implied discount rate can be calculated⁶. The corresponding implied discount rate is listed in the last column of Table 3.

⁶ Following the standards in existing literature, when calculating the discount rate linear utility function is assumed. For example for Row 6, set the net present value of the total cost of Option A equal to that of Option B: $1200 + 300/r * (1 - 1/(1+r)^{10}) = 1600 + 180/r * (1 - 1/(1+r)^{10})$ and solve for $r = 0.273$. Here $1/r * (1 - 1/(1+r)^{10}) = 1/r + 1/r^2 + 1/r^3 \dots + 1/r^{10}$, which is a factor to calculate the present value of yearly annuity for 10 years.

Table 3. The time preference elicitation experiment

Consider yourself in a situation where you must purchase an essential home electric appliance. Assume that there are two types of this appliance available. *Option A* has a lower purchase price, but consumes more energy than *Option B*. Suppose that these appliances are identical in every other way, except for the difference in purchase price and the energy cost per year. The lifetime of these two appliances are both 10 years. In each of the 15 decision situations, *Option A* has a purchase price of \$1200 and annual energy costs of \$300 and *Option B* has a purchase price of \$1600 and annual energy costs of \$X, where \$X differs in each decision row. For example, consider decision situation #4. In this situation you have a choice between an appliance that costs \$1200 to purchase and \$300 of energy a year to operate (*Option A*) or an appliance that costs \$1600 to purchase and \$220 of energy a year to operate (*Option B*). Please make 15 decisions (one for each decision situation) by choosing your 15 most preferred options.

Decision Situation	Option A		Option B		Implied Discount Rate ¹
	Purchase Price	Annual Energy Cost	Purchase Price	Annual Energy Cost	
1	\$ 1200	\$ 300	\$ 1600	\$ 280	-0.11
2	\$ 1200	\$ 300	\$ 1600	\$ 260	0.00005
3	\$ 1200	\$ 300	\$ 1600	\$ 240	0.081
4	\$ 1200	\$ 300	\$ 1600	\$ 220	0.151
5	\$ 1200	\$ 300	\$ 1600	\$ 200	0.214
6	\$ 1200	\$ 300	\$ 1600	\$ 180	0.273
7	\$ 1200	\$ 300	\$ 1600	\$ 160	0.329
8	\$ 1200	\$ 300	\$ 1600	\$ 140	0.384
9	\$ 1200	\$ 300	\$ 1600	\$ 120	0.438
10	\$ 1200	\$ 300	\$ 1600	\$ 100	0.49
11	\$ 1200	\$ 300	\$ 1600	\$ 80	0.542
12	\$ 1200	\$ 300	\$ 1600	\$ 60	0.594
13	\$ 1200	\$ 300	\$ 1600	\$ 40	0.645
14	\$ 1200	\$ 300	\$ 1600	\$ 20	0.696
15	\$ 1200	\$ 300	\$ 1600	\$ 0	0.747

¹ This column was not shown to the survey participants.

3.3 Energy related questions

Following the risk and time preferences experiments, the survey elicited a wide range of energy related characteristics including home features and energy consumption patterns. Information on home age, size, and number of residents; home location; and energy bills was gathered. Basic

sociodemographic information was also surveyed⁷. Each homeowner was asked whether they are enrolled in TOU and have a programmable thermostat. For assessing adverse selection problems, questions covered household energy patterns in terms of consuming the majority of energy during peak hours when on a flat electricity pricing scheme. With energy-related decisions reflecting environmental consciousness, questions covered turning air-conditioning or heating off when not at home, and whether the household owns an energy-efficient car. Homeowners' expectation on how long they will stay at their current home could potentially influence their decisions to adopt programmable thermostats due to the limited payback period. Thus, questions also covered the probability of moving within the next five years and when they last moved. Split incentive problems between homeowners and renters may influence households' energy-related decisions (Gillingham et al., 2012; Qiu et al., 2014b); thus, information on whether households rent part of their homes was also asked.

4. Data and descriptive statistics

Of the 398 valid survey responses, 136 and 262 are from Arizona and California, respectively. The summary statistics for Arizona and California households are presented in Tables 4 and 5. Approximately 35% of the Arizona households are enrolled in TOU, while only 19% of those in California are, and approximately 70% of the participants in both Arizona and California have adopted programmable thermostats. The average elicited CRRA coefficient is 0.81 and 0.89 for

⁷ Age, education, and retirement status are just for the respondent, not the average household. Because the decisions in a household are typically made by adults that own the property (in our survey we screen the respondents to be 21+ and own a house/condo), the ages, education levels, and retirement status of all adults that own the property should be similar or at least correlated, making the age, education level, and retirement status of the respondent representative of those for all adults responsible for decisions in the household.

Arizona and California, respectively, which is categorized as very risk averse according to Holt and Laury (2002). This is in the same range as the CRRA coefficient elicited in Andersen et al. (2008). The implied household discount rate is 16% to 17% for the two states, which indicates a general level of household impatience relative to the real return on investment.

Approximately 16% to 19% of households consume the majority of energy during peak hours when facing flat (linear) electricity pricing. In both states, 10% of households own an energy efficient vehicle such as a hybrid or electric. For Arizona households, 81% turn their air-conditioner or heater off when not at home, while in California only 47% do. This difference may result from the milder California climate not requiring as much air conditioning. In terms of mobility, 18% to 21% of households might move in the next five years, and the average years since their last move is 12 and 18 years in Arizona and California, respectively. Only 1% of homeowners in Arizona rent part of their house compared with 5% in California.⁸

Table 4. Summary statistics of household and home energy characteristics for Arizona (n=136)

Variable	Mean	Standard Deviation	Minimum	Maximum
Enroll in TOU	0.35	0.48	0	1
Have programmable thermostat	0.67	0.47	0	1
Risk (CRRA coefficient.)	0.81	0.82	-1.33	3
Time preference (discount rate)	0.16	0.22	-0.11	0.747
Incentives available to adopt energy efficient appliances	0.29	0.45	0	1
Consume majority energy during peak hours when on flat electricity prices	0.19	0.39	0	1
Turn AC or heating off when not home	0.81	0.39	0	1
Own an efficient car	0.10	0.30	0	1

⁸ Appendix Table A.1 compares the survey demographics with Census data in Arizona and California. As listed in Table A.1, there are some differences, which is primarily accounted by only sampling homeowners over 21 years old. Other potential factors including limited sample size and only sampling Internet users might also cause some difference.

Move probability	0.18	0.29	0	1
Years of residence	11.89	9.84	0	43
Sharing home with tenants	0.01	0.12	0	1
Energy bill	149.43	78.79	0	420
Age	45.28	10.76	21	66
Education	15.10	1.80	10	20
Income (in \$1000s)	64.41	42.83	5	250
Home size (1000s of sq ft)	2.06	2.52	0.05	30
Residents	2.04	1.00	1	6
Suburban home	0.59	0.49	0	1
Urban home	0.22	0.42	0	1
Age of home	24.57	15.02	3	62
Retired	0.01	0.12	0	1

Table 5. Summary statistics of household and home energy characteristics for California (n=262)

Variable	Mean	Standard Deviation	Minimum	Maximum
Enroll in TOU	0.19	0.39	0	1
Have programmable thermostat	0.71	0.45	0	1
Risk (CRRRA coefficient.)	0.89	0.94	-1.33	3
Incentives available to adopt energy efficient appliances	0.42	0.50	0	1
Time preference (discount rate)	0.17	0.22	-0.11	0.747
Consume majority energy during peak hours when on flat electricity prices	0.16	0.37	0	1
Turn AC or heating off when not home	0.47	0.50	0	1
Own an efficient car	0.10	0.30	0	1
Move probability	0.21	0.32	0	1
Years of residence	17.79	12.14	0	58
Sharing home with tenants	0.05	0.22	0	1
Energy bill	143.21	111.09	0	800
Age	43.51	11.87	21	67
Education	15.36	2.19	10	20
Income (in \$1000s)	83.49	53.01	5	250
Home size (1000s of sq ft)	1.80	0.88	0.11	11.1
Residents	2.21	1.09	1	7
Suburban home	0.65	0.48	0	1
Urban home	0.17	0.38	0	1
Age of home	37.95	19.88	1.5	116
Retired	0.00	0.06	0	1

5. Econometric models and results

To explore the influences affecting households' decisions to enroll in TOU programs, the hypotheses listed in Table 1 are tested using two separate probit models (Table 6) and one bivariate probit model (appendix Table A.2). The first probit model classifies the TOU enrollment decision with the dependent variable equal to 1 if enrolled in TOU and 0 if not. The second probit model classifies the programmable thermostats with the dependent variable 1 if a household has adopted a programmable thermostat and 0 if not. In both probit models, explanatory variables include home characteristics, sociodemographic, energy consumption patterns, and household risk and time preferences. The probit model is specified as:

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases},$$

$$y_i^* = \beta_0 + \beta_1 Risk_i + \beta_2 Time_i + \beta_3 Peak\ hour\ energy_i + \mathbf{X}_i \boldsymbol{\beta}_4 + \varepsilon_i,$$

where y_i is the binary dependent variable; y_i^* is the latent variable; the subscript i indicates an individual household; *Risk* is the CRRA risk aversion coefficient; *Time* is the implied household discount rate; *Peak hour energy* (a surrogate for adverse selection) is whether the household consumes a majority of its energy during peak hours when on flat (linear) electricity prices; $\mathbf{X}$ is a vector of conditioning household attributes; and ε is the error term assumed to be normally distributed. The economic theoretical meaning of the latent variable is the change in electricity expenditure or the negative of the compensation variation as described in Section 2. If the electricity expenditure without enrolling in TOU or adopting a programmable thermostat is greater than that with TOU or a programmable thermostat, the household will then select into TOU or adopt a programmable thermostat.

With programmable thermostats theoretically indicating enhanced TOU enrollment, the decisions to enroll in TOU programs and adopt programmable thermostats are hypothesized to be correlated. If there is no correlation, it could indicate information asymmetry where households lack the appropriate knowledge of how programmable thermostats can help them achieve better responses to TOU and thus more certain bill savings. In such case, policies and programs directed toward educating households on the role of programmable thermostats in TOU appear warranted.

This hypothesized correlation is examined in a bivariate probit framework

$$y_i^1 = \begin{cases} 1 & \text{if } y_i^{1*} > 0 \\ 0 & \text{otherwise} \end{cases},$$

$$y_i^{1*} = \beta_0^1 + \beta_1^1 Risk_i + \beta_2^1 Time_i + \beta_3^1 Peak\ hour\ energy_i + \mathbf{X}_i \boldsymbol{\beta}_4^1 + \varepsilon_i^1,$$

$$y_i^2 = \begin{cases} 1 & \text{if } y_i^{2*} > 0 \\ 0 & \text{otherwise} \end{cases},$$

$$y_i^{2*} = \beta_0^2 + \beta_1^2 Risk_i + \beta_2^2 Time_i + \beta_3^2 Peak\ hour\ energy_i + \mathbf{X}_i \boldsymbol{\beta}_4^2 + \varepsilon_i^2,$$

$$\begin{pmatrix} \varepsilon_i^1 \\ \varepsilon_i^2 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right],$$

where y_i^1 and y_i^2 are the indicator variables for TOU enrollment and adopting programmable thermostats, respectively; errors ε_i^1 and ε_i^2 are assumed to be normally distributed with an associated covariance matrix. If ρ is significantly different from zero, then the two decisions are correlated.

TOU programs are different in design based on different electric utilities. The definition of peak hours, the price levels, and other fixed charges can be different. Within an electric utility company, there could be multiple TOU programs, which are different in design. In our study, we do not know the details of the TOU programs for the participants so we cannot consider TOU

program specific controls. However, we use zip-code clustered standard errors to take into consideration that households within the same zip code might be correlated in terms of TOU participation. This correlation may result from zip-code level factors such as utility service territory, neighborhood energy infrastructure development, and peer effects from neighbors.

Table 6. Probit models for the decisions to enroll in TOU and to adopt programmable thermostats

	Enrolled in TOU		Programmable Thermostat	
	Coefficient	Marginal Effects	Coefficient	Marginal Effects
Risk (CRRRA coefficient)	-0.148*	-0.045*	-0.070	-0.024
	(0.088)	(0.026)	(0.078)	(0.026)
Time preference (discount rate)	0.234	0.071	-0.942***	-0.321***
	(0.330)	(0.100)	(0.313)	(0.107)
Peak hour energy	-0.413*	-0.112**	0.144	0.048
	(0.220)	(0.052)	(0.197)	(0.063)
Turn AC or heating off when not home	-0.070	-0.021	0.154	0.053
	(0.161)	(0.049)	(0.149)	(0.051)
Own an efficient car	-0.204	-0.058	0.045	0.015
	(0.251)	(0.067)	(0.234)	(0.078)
Move probability	0.239	0.072	-0.090	-0.031
	(0.237)	(0.072)	(0.239)	(0.081)
Years of residence	-0.002	-0.001	-0.006	-0.002
	(0.007)	(0.002)	(0.007)	(0.002)
Sharing home with tenants	0.020	0.006	0.207	0.066
	(0.412)	(0.127)	(0.367)	(0.110)
Energy bill	-0.0003	-0.00007	0.0001	0.00004
	(0.001)	(0.0002)	(0.001)	(0.0003)
Age	0.018**	0.005**	0.007	0.002
	(0.008)	(0.002)	(0.007)	(0.002)
Education	0.014	0.004	0.028	0.010
	(0.034)	(0.010)	(0.034)	(0.011)
Income (in \$1000s)	0.001	0.0003	0.001	0.0003
	(0.002)	(0.001)	(0.002)	(0.001)
Home size (1000s of sq. ft.)	-0.020	-0.006	0.131	0.044
	(0.032)	(0.010)	(0.111)	(0.037)
Number of Residents	0.198***	0.060***	0.136*	0.046*

	(0.076)	(0.023)	(0.074)	(0.025)
Suburban home	0.108	0.032	0.503***	0.176***
	(0.206)	(0.061)	(0.180)	(0.064)
Urban home	0.164	0.051	0.634***	0.188***
	(0.254)	(0.082)	(0.228)	(0.057)
Age of home	-0.004	-0.001	-0.007*	-0.002*
	(0.004)	(0.001)	(0.004)	(0.001)
Retired	-0.382	-0.099	-0.142	-0.050
	(0.743)	(0.159)	(0.700)	(0.255)
Arizona	0.525***	0.167***	-0.309*	-0.108*
	(0.183)	(0.061)	(0.170)	(0.061)
Constant	-2.114***		-0.664	
	(0.732)		(0.711)	
Number of observations	398		398	
Log likelihood	-205.75		-226.37	
Wald Chi2 statistic	28.56		30.19	

Zip-code clustered standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

5.1 Probit model: TOU

As developed theoretically in Table 1, it is hypothesized that more risk averse households are less likely to participate in TOU programs and, with no sunk costs for enrollment, there are no intertemporal monetary decisions. Time preferences should then not play a significant role, so the associated coefficient is expected to be statistically insignificant. If there is an adverse selection problem in participating in a TOU program, the coefficient associated with *Peak hour energy* will be negative. Theoretically, if a household consumes a higher proportion of energy during peak hours, they will be less likely to enroll in TOU programs.

The results support these hypotheses—the associated risk aversion is statistically significant and negative at the 10% level, indicating that risk-averse households are less likely to enroll in TOU programs. As hypothesized, the time preference coefficient is not statistically

significant at the 10% level. The coefficient for *Peak hour energy* is statistically significant and negative at the 10% level. Based on the associated marginal effects, if a household consumes a higher proportion of electricity during peak hours, the probability of enrolling in TOU will be 11% lower than it is for households who do not. This suggests that an adverse selection problem exists in voluntary TOU program participation.

For the other statistically significant coefficients, the variable *Number of Residents* has a positive impact on enrolling in TOU. As the number of residents increase, there could be enhanced opportunities to shift energy consumption from peak hours to nonpeak hours. This would yield greater benefit from TOU. *Age* of the household head also has positive and statistically significant impact at the 5% level. Older households potentially have had greater exposure to TOU. This could be through their utility companies and/or from their neighbors. Arizona households have a greater likelihood to enroll in TOU programs relative to those in California. This is possibly due to the relatively hotter climate, which requires more air-conditioning and thus provides a larger potential for adjusting to TOU through avenues such as precooling. Further, Arizona's peak summer energy hours are in late afternoon, whereas California's peak hours are in the evening. Thus, it is easier for Arizona residents to adjust to TOU, which provides additional indirect adverse selection evidence.

Interestingly, the marginal effects indicate that adverse selection variables are the strongest predictors of TOU enrollment. Peak hours of energy use and the Arizona dummy variable exert the largest influence. Adverse selection appears to have a strong presence in voluntary TOU enrollment. Policymakers should be aware of this presence when designing policies and programs. In particular, the presence of adverse selection results in policy slippage. Not considering its presence will result in reductions in power company peak-hour energy demand that are less than

predicted. This may require adjusting nonlinear and linear prices and developing public educational programs directly addressing households' possible perceived uncertainties. Higher linear energy pricing essentially converts a voluntary TOU program to a mandatory program with the penalty of facing a higher price for energy.

5.2 Probit model: Programmable thermostats

As theoretically hypothesized (Table 1), risk aversion is not statistically significant at the 10% level. This result is in contrast to other research finding of a significant impact of risk aversion on adoption of energy efficient measures such as washers and attic insulation (Qiu et al., 2014a). The unique risk-reducing feature of programmable thermostats may explain this contradiction. For energy efficiency investments, there are two types of risk: whether the investment can actually save energy and how much energy can be saved. For other types of energy efficient technologies, both risks exist. For programmable thermostats, the temperature set by the thermostat is certain, and thus, the energy savings are less risky. As a result, risk aversion appears to not impact the decision to adopt programmable thermostats.

In contrast, time preference does have a significant negative impact at the 1% level. Up-front capital costs of programmable thermostats range from \$50 to \$250 each, with energy cost savings only occurring in the future. This intertemporal decision requires discounting future lower energy bills based on each household's implicit time preference for money. Results support the hypothesis that higher discount rates will result in lower discounted future energy bills, and thus less likelihood that a household will adopt programmable thermostats.

Considering other factors, the *Number of Residents* is significant and positive at the 10% level. Similar to the probit TOU model, this could be the result of a larger potential to save on energy bills when there are more people in the household. Suburban and urban households have a greater likelihood relative to rural ones to adopt programmable thermostats. Within suburban and urban areas, this result could be explained by the existence of more channels for purchasing and adopting the thermostats along with greater opportunities to be exposed to the technology. The coefficient associated with *Age of home* is significant and negative at the 10% level. As new homes become more energy efficient, they are more likely to already have programmable thermostats. Finally, Arizona homes are less likely to adopt programmable thermostats compared with California homes, which could be due to differences in the environmental preferences of the state's households.

Turning to marginal effects, time preference for money is the dominant variable in predicting the likelihood for adopting thermostat technical change. The associated coefficient in absolute value is approximately twice that of other significant coefficients. The revealed household implicit discount rates, listed in Tables 4 and 5, exceed values employed in engineering to determine life-cycle costs in evaluating the tradeoff of increased energy conservation and lower operating costs against higher initial capital costs. Thus, forecasts of household demand for energy efficient appliances may be too optimistic. Results indicate that households may have higher discount rates than the socially determined market rate. This divergence can be narrowed by a subsidy on initial capital costs. Such a subsidy could take the form of a tax credit, which is currently available for many energy-efficient technologies.

5.3 Bivariate model on TOU pricing and programmable thermostats

The results of the bivariate probit model, listed in Appendix Table A.2, yields a statistically insignificant correlation parameter ρ between TOU enrollment and programmable thermostat adoption. This lack of significance is contrary to economic theory; the purchase of a programmable thermostat does not appear to positively impact TOU enrollment. One explanation of this theory/empirical inconsistency is the results indicate newer, urban, and suburban homes are more likely to adopt programmable thermostats, while these factors do not influence whether households enroll in TOU programs (Table 6). The bundling of a new home purchase with a programmable thermostat does not necessarily mean a household was willing to pay the threshold market price for the thermostat. Some households in this bundled purchase may have a very low willingness to pay for a programmable thermostat. They may not even take the time to program the thermostat, so their consumer surplus from the thermostat is zero. Thus, as theory would indicate, there is no augmentation of any TOU surplus from having a programmable thermostat. This indicates households might not be aware of the role of programmable thermostats in responding to TOU. Policymakers may want to address this possible broken link through education programs that indicate the potential savings from integrating programmable thermostats with TOU.

5.4 Other model specifications

In addition to a bivariate probit model, we also conduct an instrumental variable (IV) probit model to analyze the relationship between the enrollment in the TOU programs and the adoption of programmable thermostats. In this model, the endogenous variable is the adoption of programmable thermostats and the IV is whether incentives are available to adopt energy efficient

appliances. IV is likely to influence the adoption of programmable thermostat because programmable thermostat is one type of energy efficient appliance. It will not directly influence the participation of TOU programs, because a TOU program is not an appliance. IV will influence the participation of TOU programs only through the adoption of programmable thermostats. The results of the IV probit model are listed in Appendix A.3 and indicate there is no statistically significant relationship between the adoption of programmable thermostats and the enrollment in TOU programs. The Wald test of endogeneity indicates the variable of adopting programmable thermostat is exogenous. Thus, we base our discussion on the results of simple probit models.

For robustness checks, we also run probit models with quadratic terms of the demographics variables (Table A.4). Across the different model specifications, we find consistent coefficient signs and significance levels. Our results are consistent with existing literature. For the very few studies that analyze TOU participation, there is weak or no statistically significant relationship between household characteristics and participation in TOU programs (Caves et al., 1989). In addition, previous literature attempting to explain the influence of building characteristics and sociodemographics on household electricity consumption have also found only a weak or nonexistent relationship (e.g., Huebner et al. 2015). Our own interpretation is human factors that researchers commonly observe typically have dual effects. For example, we agree, households with higher energy bills should be more likely to enroll in TOU because they have they have the potential for reducing the monthly financial expenditure. But, by the same coin, the fact that those households have higher energy bills could be because they are less engaged in reducing their energy bills and thus less likely to enroll in TOU. As well, we agree, “turning AC or heating off when not home” is an indication of energy saving awareness, which should be positively correlated with TOU. However, by the same coin, those households who are active in making sure they turn

off the AC or heating when not at home are potentially individuals who are home more often, and hence would benefit least from TOU.

6. Discussion and policy implications

Results indicate that adverse selection exists in the participation of voluntary TOU programs, where households who consume limited energy during peak hours tend to enroll in TOU programs. This is related to current policy debates on whether TOU should be universally mandatory adopted or voluntary. If adverse selection exists for voluntary programs and these self-selected participants only slightly shift away from peak hour electricity consumption, then the expected benefit from load shifting behavior would be lower than expected. Such losses are likely to be passed through to customers. However, these self-selected households may to some degree respond to TOU. Thus, for every voluntary TOU program, an economic assessment is warranted that addresses its impact on electricity consumption patterns and welfare. Existing literature on voluntary programs has mixed results. Aigner and Ghali (1989) find that self-selection can generate bias for estimating the impact of TOU programs. Caves et al. (1989) find that voluntary TOU programs actually have larger shifts in peak hour energy consumption than mandatory programs do. They identify another type of selection bias, where consumers that have better ability to respond to a TOU program tend to enroll. Baladi et al. (1998) find that voluntary and mandatory TOU programs do not differ significantly in their impacts. Train and Mehrez (1994) find that a voluntary TOU program does not constitute a Pareto improvement. This study adds to the existing studies on self-selection and participation of TOU programs by directly providing evidence of adverse selection of participation through survey of participants' characteristics including pre-participation peak hour energy use and econometric analysis of the survey results, while existing studies mostly focus on evaluating the impact of voluntary TOU programs and for those that do analyze the participation, only

descriptive statistics of pre-participation energy use are presented. For policymakers, it is important to determine the optimal set of controls (policies) under their discretion. Markets and households will respond to both good and bad policies. Care is then required in setting the TOU nonlinear pricing relative to linear pricing and determining the particular educational programs that will modify household preferences toward energy and environmental efficiency.

Results indicate that risk preference is a strong predictor of TOU enrollment. A potential avenue through which utility companies can help (i) mitigate the impact of risk aversion on participation in TOU programs and (ii) reduce the perceived risk of TOU programs is by harnessing peer effects. Previous literature has indicated that individual behavior and decisions in risky settings are affected by information on the behavior of their peers and whether decisions are made jointly or as a group. Studies indicate that participants were willing to take more risks and paid more attention to the benefits than the costs of risky behavior, and their decisions were riskier, when in peer groups (Gardner and Steinberg, 2005). The influence of peers plays a crucial role in program participation, and peer effects are an important mechanism for the transmission of information about the costs and benefits of programs (Dahl et al., 2014). Thus, by facilitating the transfer of information about TOU programs and realized energy cost savings among peer households, there is the potential to reduce households' perceptions of TOU program risks and ultimately reduce this barrier to program adoption. Some utility and energy companies already have programs that utilize peer effects. For example, a number of US companies, including Opower and Salt River Project, have sent households information about their energy consumption relative to their neighbors and households with similar attributes. The results of this study suggest that utility companies could further expand this peer information to aid in encouraging households to participate in TOU programs by adding two more pieces of information: (i) how many of their

neighbors have participated in TOU programs and (ii) how much their neighbors' energy bills have been reduced through TOU. By providing such information to peer households, the negative impact from risk aversion could be mitigated.

Results indicate that household time preference for money (an implied discount rate) has a negative impact on adopting programmable thermostats. This is closely related to the energy efficiency paradox, where cost-effective energy efficient technologies based on net present value calculations at current prices enjoy only limited market success (Brown, 2001; Jaffe and Stavins, 1994). As indicated from the results, households applying higher implied discount rates relative to socially determined market rates may explain this paradox. From a social perspective, households may be myopic. Specifically, the higher households' implied discount rates are, the less likely they will be to invest in programmable thermostats. For policymakers, it is then important to clear any potential barriers that might cause abnormally high implied discount rates in evaluating programmable thermostats. Barriers include imperfect information and inattention (Allcott and Greenstone, 2012), which could be addressed through government or utility information and educational programs. In addition, some utilities and states provide rebates for installing programmable thermostats, which can also help alleviate the impact of time preferences.

The bivariate probit model results indicate that decisions to enroll in TOU programs and adopt programmable thermostats are not correlated. One possible explanation is that the households might lack the knowledge that programmable thermostats can enable better response to TOU. Further research is needed in order to provide direct evidence for this hypothesis. Utility companies could provide education or information provision programs targeting the relation between TOU and programmable thermostats.

8. Conclusion

Time-invariant (linear) electricity pricing does not reflect daily variation in the cost of producing electricity, and thus can cause economic inefficiency. TOU (nonlinear) pricing, with higher electricity prices during peak hours and lower prices during nonpeak hours, attempts to equate prices to marginal costs. This will improve both the intertemporal production and consumption of electricity consumption. TOU can either be voluntary or mandatory. There is a current policy debate concerning whether TOU should be voluntary or mandatory. This study examines the factors influencing households' participation in TOU programs, which is addressed only to a limited extent in existing literature. In addition, the examination of household adoption of programmable thermostats is investigated, as they act as an enabler to better respond to TOU.

Employing multiple price-list experiments, household risk and time preferences are elicited. These elicited preferences are then employed to explain households' self-reported enrollment in TOU programs and adoption of programmable thermostats. Employing data from 398 homeowners in Arizona and California, results indicate that more risk averse households are less likely to enroll in TOU programs. This result supports the developed underlying economic theory relating risk aversion and TOU enrollment. The results also support the theory of adverse selection in TOU programs. Households who do not consume much energy during peak hours are found to be more likely to enroll in TOU programs. These households do not have to greatly modify their energy consumption preferences in order to save on their energy bills. Time preferences are found to have a statistically significant and negative impact on household adoption of programmable thermostats. The initial sunk cost commitment of such technologies and associated future benefits underlies this result. In addition, results indicate no evidence that households' decisions to enroll in TOU programs and to adopt programmable thermostats are correlated.

Results have important implications for policymakers. Evidence of adverse selection implies the possibility of net loss to utility companies that will ultimately be passed through to all customers. Thus, for every voluntary program, it is important to conduct an economic assessment of its impact on electricity consumption patterns and welfare that controls for selection bias. For promoting participation in TOU programs, utility companies can help mitigate the impact of risk aversion and reduce the perceived risk of TOU programs by harnessing peer effects. To improve the response to TOU programs, utility companies and government agencies can adopt information provisions and education programs about programmable thermostats to help with the adoption of such technologies. However, the research results from testing the theory of adverse selection have a broader implication than just TOU. It provides another empirical demonstration that the theoretical concept of adverse selection does have a significant impact on voluntary adoption.

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Appendix

Table A.1. Comparison of the demographics between the survey sample (21 years or older head of household) and census population statistics

	Arizona		California	
	Census	Survey sample	Census	Survey sample
Persons per household	2.66	2.04	2.93	2.21
Household income(\$1000s)	50.20	64.41	61.40	83.49
Age	35.90	45.28	35.20	43.51
Years of Education	15.04	15.10	15.35	15.36
Years of Residence	9.00	11.89	11.00	17.79

Table A.2. Bivariate probit models for the decisions to enroll in TOU pricing and to adopt programmable thermostat

	Enrolled in TOU	Programmable thermostat
Risk (CRRRA coef.)	-0.148*	-0.071
	(0.088)	(0.078)
Time preference (discount rate)	0.235	-0.942***
	(0.329)	(0.313)
Consume majority energy during peak hours when on flat electricity prices	-0.414*	0.144
	(0.220)	(0.197)
Turn AC or heating off when not home	-0.070	0.154
	(0.160)	(0.149)
Own an efficient car	-0.203	0.044
	(0.251)	(0.234)
Move probability	0.239	-0.090
	(0.237)	(0.239)
Years of residence	-0.002	-0.006
	(0.007)	(0.007)
Sharing home with tenants	0.020	0.205
	(0.412)	(0.367)
Energy bill	-0.0002	0.0001
	(0.001)	(0.001)
Age	0.018**	0.007
	(0.008)	(0.007)
Education	0.014	0.028
	(0.034)	(0.034)
Income (in \$1000s)	0.001	0.001
	(0.002)	(0.002)
Home size (1000s of sq. ft.)	-0.020	0.132
	(0.032)	(0.110)
Residents	0.198***	0.135*
	(0.076)	(0.074)
Suburban home	0.108	0.504***
	(0.206)	(0.180)
Urban home	0.164	0.634***
	(0.254)	(0.228)
Age of home	-0.004	-0.007*
	(0.004)	(0.004)
Retired	-0.382	-0.142
	(0.743)	(0.699)
Arizona	0.525***	-0.309*
	(0.183)	(0.170)
Constant	-2.112***	-0.665
	(0.733)	(0.710)

ρ	-0.012 (0.095)
Number of observations	398
Log likelihood	-432.11
Wald chi2	64.66

Zip-code clustered standard errors in parentheses: * p < 0.1, ** p < 0.05, and *** p < 0.01.

Table A.3. Instrumental variable probit model for the decisions to enroll in TOU pricing (instrumental variable: received; instrumented variable: adopting programmable thermostat)

	First stage	Second stage
	Programmable thermostat	Enrolled in TOU
Incentives available to adopt energy efficient appliances	0.180*** (0.047)	
Adopted programmable thermostat		0.101 (0.850)
Risk (CRRA coef.)	-0.022 (0.025)	-0.145* (0.086)
Time preference (discount rate)	-0.339*** (0.101)	0.267 (0.423)
Consume majority energy during peak hours when on flat electricity prices	0.058 (0.062)	-0.418* (0.220)
Turn AC or heating off when not home	0.035 (0.048)	-0.075 (0.167)
Own an efficient car	-0.005 (0.074)	-0.205 (0.248)
Move probability	-0.024 (0.072)	0.241 (0.234)
Years of residence	-0.002 (0.002)	-0.002 (0.008)
Sharing home with tenants	0.078 (0.116)	0.013 (0.386)
Energy bill	0.0002 (0.0003)	-0.0002 (0.001)
Age	0.002 (0.002)	0.018** (0.008)
Education	0.006 (0.011)	0.013 (0.038)

Income (in \$1000s)	0.0002 (0.0005)	0.001 (0.002)
Home size (1000s of sq. ft.)	0.017 (0.014)	-0.022 (0.051)
Residents	0.037 (0.025)	0.193** (0.091)
Suburban home	0.174*** (0.060)	0.090 (0.250)
Urban home	0.210*** (0.075)	0.142 (0.312)
Age of home	-0.002* (0.001)	-0.004 (0.005)
Retired	0.011 (0.259)	-0.375 (0.832)
Arizona	-0.075 (0.054)	0.535*** (0.192)
Constant	0.349 (0.222)	-2.144*** (0.782)
Wald test of exogeneity (/athrho = 0): chi2(1) = 0.02 Prob > chi2 = 0.8953		

Table A.4. Probit models for the decisions to enroll in TOU and to adopt programmable thermostats, with square terms of demographic variables

	Enrolled in TOU		Programmable Thermostat	
	Coefficient	Marginal Effects	Coefficient	Marginal Effects
Risk (CRRA coefficient)	-0.155* (0.088)	-0.044* (0.025)	-0.073 (0.079)	-0.023 (0.025)
Time preference (discount rate)	0.194 (0.343)	0.056 (0.098)	-0.903*** (0.315)	-0.291*** (0.099)
Peak hour energy	-0.386* (0.222)	-0.111* (0.063)	0.138 (0.199)	0.044 (0.064)
Turn AC or heating off when not home	-0.083 (0.163)	-0.024 (0.047)	0.155 (0.149)	0.050 (0.048)

Own an efficient car	-0.104 (0.259)	-0.030 (0.074)	0.004 (0.239)	0.001 (0.077)
Move probability	0.231 (0.236)	0.066 (0.067)	-0.087 (0.239)	-0.028 (0.077)
Years of residence	-0.001 (0.007)	-0.0003 (0.002)	-0.007 (0.007)	-0.002 (0.002)
Sharing home with tenants	0.032 (0.422)	0.009 (0.121)	0.205 (0.371)	0.066 (0.120)
Energy bill	-0.0004 (0.001)	-0.0001 (0.0002)	0.0002 (0.001)	0.00005 (0.0003)
Age	0.028 (0.034)	0.005* (0.003)	0.018 (0.030)	0.002 (0.003)
Age^2	-0.0001 (0.0004)		-0.0001 (0.0004)	
Education	1.070** (0.450)	0.010 (0.010)	-0.271 (0.370)	0.007 (0.011)
Education^2	-0.034** (0.014)		0.010 (0.012)	
Income (in \$1000s)	-0.001 (0.005)	0.0002 (0.001)	0.003 (0.004)	0.0005 (0.001)
Income^2	0.00001 (0.00002)		-0.00001 (0.00002)	
Number of Residents	-0.025 (0.250)	0.042 (0.029)	0.173 (0.255)	0.045 (0.032)
Number of Residents^2	0.039 (0.040)		-0.008 (0.042)	
Home size (1000s of sq. ft.)	-0.014 (0.032)	-0.004 (0.009)	0.128 (0.109)	0.041 (0.035)
Suburban home	0.096 (0.205)	0.027 (0.059)	0.508*** (0.181)	0.164*** (0.056)
Urban home	0.196 (0.253)	0.056 (0.073)	0.630*** (0.230)	0.203*** (0.072)
Age of home	-0.005 (0.005)	-0.001 (0.001)	-0.007 (0.004)	-0.002 (0.001)
Retired	-0.271 (0.845)	-0.078 (0.243)	-0.081 (0.739)	-0.026 (0.238)
Arizona	0.494*** (0.183)	0.142*** (0.052)	-0.293* (0.171)	-0.095* (0.055)
Constant	-10.075*** (3.580)		1.309 (3.027)	
Number of observations	398		398	
Log likelihood	-202.59		-225.85	
Wald Chi2 statistic	36.97		31.72	

Zip-code clustered standard errors in parentheses: * p < 0.1, ** p < 0.05, and *** p < 0.01.

Note: Hypothesis testing of partial effects for interaction terms in non-linear models is not necessarily informative and can be potentially misleading (Ai and Norton, 2003; Greene, 2010), thus we do not calculate the marginal effects for the square terms.