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Increasing voluntary enrollment in time-of-use electricity rates: Findings from a survey experiment

Corey Lang

Yueming Lucy Qiu

Luran Dong

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Corey Lang[*], Yueming (Lucy) Qiu, Luran Dong

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Abstract

Relative to flat rate pricing, time-of-use (TOU) electricity rates improve alignment of household incentives to reduce electricity consumption during times when the wholesale cost of electricity is expensive. This research seeks to understand factors of the TOU plan that impact voluntary enrollment with the purpose of identifying levers that are at the disposal of a utility to increase voluntary enrollment. We conducted an survey experiment of people living in the United States. The survey randomized the peak to off-peak price ratios, the peak hours, and the number of TOU plans being offered. Our results indicate several policy-relevant findings. On average, when only one TOU plan is offered, the peak to off-peak price ratio has no impact on enrollment decisions. Respondents who are offered more than one TOU plan are 14.2 percentage points more likely to enroll than respondents only offered one TOU plan, which suggests that the ability to compare TOU plans is an important mechanism. Further, when multiple plans are presented, the average respondent is price responsive, preferring TOU plans with a large peak to off-peak price ratio (larger price spread). Lastly, people prefer shorter on-peak period lengths when either one or multiple plans are offered.

Keywords: time-of-use electricity rate; survey; decoy effect; status quo bias; peak to off-peak price ratio

JEL codes: C91; L94; Q41

[*] Contact author: 214 Coastal Institute, 1 Greenhouse Rd., University of Rhode Island, Kingston, RI, 02881. Email: clang@uri.edu.

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1. Introduction

It has been widely recognized that time-invariant retail electricity pricing can cause economic inefficiency for the electricity market due to the misalignment between consumer incentives and the marginal cost of electricity supply (Borenstein and Holland 2005; Williamson 1966). Time-invariant pricing such as flat-rate or increasing block pricing provides no intra-day variation in pricing incentives for consumers to adjust their electricity consumption behaviors throughout a day. However, the marginal cost of providing electricity to residential consumers varies by time of day (Steiner 1957). Typical types of power plants used for base electric load supply— power plants that are running throughout a day— are coal-fueled or nuclear plants due to the steady-state power and low-cost fuel (Holland and Mansur 2008). Peak load power plants are used to supply electricity during peak hours only such as late afternoon and early evening hours in the summer, and these power plants need to have the ability to ramp up quickly to meet the sharp increase in demand in these hours and can also be easily stopped (Eisenack and Mier 2019). Typical peak load power plants include natural gas and oil power plants.

The marginal cost of fuel of peak power plants is generally more expensive than that of the baseload power plants. As a result, time-invariant pricing can cause consumers to overconsume electricity during peak hours when the cost of supplying electricity is high and under-consume during off-peak hours when the cost of supplying electricity is low. In addition, utility companies need to ensure the reliability of the power grid. The capacity of the power grid infrastructure is sized based on the peak hour electricity demand. If the electricity demand during peak hours exceeded the capacity, blackouts will happen. If consumers do not face the adequate incentives to reduce peak hour demand, it can create a large pressure for grid reliability if system peak hour demand continues to increase.

Due to these reasons, economists have argued that time-variant pricing schemes such as real-time pricing, critical peak pricing, critical peak rebate, and time-of-use pricing (TOU) plans are generally considered as welfare-improving because their prices better reflect the intra-day variation in the cost of supplying electricity (Allcott 2011, Wolak 2011). These price plans can help utilities flatten their electric load curves to increase the supply of electricity with cheaper marginal cost, reduce the supply of electricity with higher marginal cost, and better maintain grid stability. This study focuses on TOU pricing because it is more common compared to the other time-variant pricing due to its relative simplicity (Wolak 2011). TOU pricing generally divides a day into several time windows, namely peak hours, off-peak hours, and/or shoulder peak hours. The peak hours are generally in line with the hours of higher electric demand such as late afternoon and early evening in the summer, and early morning hours in the winter. Off-peak hours are hours with lower electricity demand. The marginal electricity price in peak hours is higher than that in the off-peak hours. Customers respond to the price incentives and shift load to off-peak hours (Fowlie et al. 2021), which in turn can reduce supply costs.

Even though TOU pricing better reflects the varying cost of electricity supply, most utilities do not implement mandatory TOU price plans due to concerns such as customer satisfaction and potential increased electricity bill burdens for consumers that do not load shift

(Jessoe et al. 2014, Parrish 2013). TOU price plans implemented currently are mostly voluntary, but unfortunately the enrollment rate of voluntary TOU programs is low (Choi et al. 2020, Fowlie et al. 2021). Thus understanding the factors that determine consumers' choice of TOU pricing is important.

Our research seeks to understand the characteristics of the TOU plan that impact voluntary enrollment with the purpose of identifying levers at the disposal of a utility to increase voluntary enrollment. We conducted an online randomized experimental survey to examine the following three main research questions that have not been answered by the existing literature:

1) *How do TOU design attributes, including length of peak hours and the on-peak to off-peak price ratio, impact consumers' TOU enrollment decisions?*
2) *How does the number of TOU plans offered to the consumers influence their TOU enrollment decision?*
3) *What are the mechanisms leading to increased enrollment when multiple TOU plans are offered?*

The answers to these questions have useful implications to inform TOU pricing designs and marketing efforts to increase the voluntary enrollment of TOU. A novel aspect of our survey is that about half of respondents see choice tasks with one TOU plan and the default flat rate plan, and the other half of respondents see choice tasks with two TOU plans and the default flat rate plan. While it is uncommon for utilities to offer two TOU plans to customers, we hypothesized that behavioral economics may yield insights into consumer choice. Offering multiple plans may increase attention or enable comparisons with a non-flat rate reference point, both of which could increase enrollment.

In fall 2020, we conducted an experimental survey on MTurk of people living in the United States that asked respondents if they would like to enroll in a TOU plan or remain on their flat rate plan. The survey randomized the on-peak to off-peak price ratios, the on-peak hours, and the number of TOU plans being offered (one or two). The survey customized all prices to the state of residence. The survey also asked about risk preferences, utility bills, and standard demographics. We collected data from 588 respondents across 38 states, which combine for a total of 1764 TOU enrollment choices.

Our results indicate several policy-relevant findings. On average, when only one TOU plan is offered, the spread between on-peak and off-peak prices has no impact on enrollment decisions. However, respondents who are offered two TOU plans are 14.2 percentage points more likely to enroll than respondents only offered one TOU plan, which suggests that the ability to compare TOU plans is an important mechanism in this decision environment. Further, when multiple plans are presented, the average respondent is price responsive. Specifically, we find that people are most likely to enroll in a TOU plan with a large peak to off-peak price ratio (larger price spread) that is simultaneously offered with a plan with a small peak to off-peak price ratio. The on-peak period length always has an impact on enrollment decisions when either one or multiple plans are offered.

2. Prior Literature and Contributions

While there has been a rich literature assessing the impact of TOU pricing on electricity consumption behaviors (Di Cosmo, Lyons, and Nolan 2014; Faruqui and Sergici 2010; Jessoe, Rapson, and Smith 2014; Qiu, Kirkeide, and Wang 2018; Prest 2020; Schittekatte et al. 2022), only a few papers have studied TOU enrollment decisions. Several studies examine the relationship between consumers' characteristics and TOU enrollment. These characteristics include risk and time preferences, renter versus owner, trust attitudes (e.g., specific trust in an electric supplier's financial stability), social preferences, political identification (e.g. left-wing versus liberal policy orientation), relocation decision, household income, households' baseline electricity consumption patterns, and households' perceived usage of various appliances (Belton and Lunn 2020; Mostafa Baladi, Herriges, and Sweeney 1998; Qiu, Colson, and Wetzstein 2017; Schleich, Faure, and Gassmann 2019; Ziegler 2020).

Field experiments have also been used to examine TOU enrollment decisions. Two such studies examine how external interventions can impact the voluntary uptake of TOU pricing. Fowlie et al. (2021) find that default effects have an enormous impact on increasing enrollment by 75 percentage points over a voluntary plan.[1] Ito et al. (2021) find that lump sum financial incentives increase voluntary enrollment by 17 percentage points. While field experiments are powerful at testing certain hypotheses, they are limited in the number of mechanisms they can test. In both Fowlie et al. (2021) and Ito et al. (2021), there is only one TOU rate plan that is offered to all customers, meaning they can say nothing about the influence of the price of plans or the number of plans on enrollment.

We contribute to this literature by assessing how TOU design attributes including on-peak and off-peak prices, on-peak start time, and on-peak duration impact enrollment decisions as well as whether offering more than one TOU plan can influence such decisions. While a hypothetical survey has drawbacks because decisions are inconsequential, our survey is an important first step to understand how utilities' plan designs may influence TOU adoption.

Our analysis of the effect of offering multiple TOU plans versus just one is also relevant to the strands of the behavioral economics literature on status quo bias and the decoy effect. Status quo bias, the tendency for people to prefer the existing state of affairs even when a change seemingly offers a Pareto improvement, is a remarkably robust finding in behavioral economics (Poe 2016). Lab experiments have shown large disparities in people's preferences for everyday items, such as coffee mugs and pens, when they are randomly given to them versus not (Kahneman et al. 1990). Status quo bias exists in much higher stakes settings too such as organ donation (Johnson and Goldstein 2003) and retirement contributions (Thaler and Benartzi 2004).[2] As previously mentioned, Fowlie et al. (2021) find strong evidence of status quo bias in preferences for electricity rate structure. While only about 25% of customers voluntarily enroll in TOU pricing, 95% of customers will stay enrolled in TOU if they are assigned to that pricing

[1] A review study also finds that opt-out enrollment can lead to a higher TOU uptake rate than opt-in enrollment (Nicolson, Fell, and Huebner 2018).

[2] Additionally, Lang et al. (2021) find that even preferences for public policies, specifically carbon mitigation, exhibit status quo bias.

scheme. We find that offering two TOU plans instead of one increases voluntary enrollment 14.2 percentage points, which is a 33.5% increase from baseline enrollment. Because flat rate is the default plan, respondents are likely to stick with it. However, we find at least some of the status quo bias effect can be mitigated by offering multiple plans.

The decoy effect is a finding that when people are deciding between two options, introducing a third ("decoy") option that is strictly dominated by one of the two initial options changes the frequency at which the first two options are chosen (Huber et al. 1982). The choice tasks in these experiments are complex and participants face tradeoffs between different dimensions of the choices. The decoy choice acts to simplify the decision task by providing a similar reference point. Additionally, Ariely and Wallsten (1995) show that importance weights of the different dimensions of choices change when a decoy is added. Our TOU choice task setting does not match the standard decoy effect exactly because the second TOU plan is not intended to be a decoy – it is not strictly dominated by the other TOU plan. However, the second TOU plan does add a reference point that simplifies the choice. Further, similar to the Ariely and Wallsten (1995) finding, when only one TOU plan is presented, prices do not matter, but when two are presented, prices do matter – the importance weight of the price dimension changes. Recent research into mechanisms behind the decoy effect point to increased attention given to choices and how attention alone can change preferences (Towal et al. 2013, Smith and Krajbich 2019). In our context, when a second TOU plan is added, it is likely that more attention is given to TOU plans, at a minimum, to understand differences. This increased attention could drive part of the shift in preferences to TOU plans.

Our results of whether consumers pay attention to on-peak and off-peak price ratio is related to the strand of literature on consumer inattention and energy-related decisions. These studies find that consumers only pay limited attention to energy costs and appliance operating features when making the purchase decisions of durable goods (Andor, Gerster, and Sommer 2020) or deciding whether to have an energy home audit (Palmer and Walls 2015). Due to inattention, some consumers are not adopting energy efficiency measures that can generate positive economic value for them. In the context of choosing to enroll in a TOU plan, a TOU plan can also potentially generate positive economic values by shifting enough electricity consumption from peak hours to off-peak hours and thus saving on electricity bills. We find that consumers are not paying attention to the price ratio when only one TOU plan is offered. However, those same plans are being enrolled in with greater frequency when multiple plans are offered. These finding together indicate that inattention to energy prices could potentially lead to sub-optimal decisions. The flip side of this, though, is that attention can be primed by offering more than one TOU option.

3. Survey and data

3.1 Survey design

We designed an experimental survey to examine if TOU plan characteristics and reference points influence people's willingness to enroll in a TOU electricity rate plan. To be clear, the survey is hypothetical and has no bearing on actual rate plans. While general concerns exist about stated preference research and hypothetical bias (Diamond and Hausman 1994), stated preference methods are generally respected and often used (Johnston et al. 2017) and several articles in this research vein have used stated preference methods (e.g., Belton and Lunn 2020; Ziegler 2020). These methods are commonly used when actual choices or key variables are difficult to observe or there is limited variation observed with real world choices. In the context of electricity rate plan choice, existing real-world TOU plan offers have very limited variation in key attributes (and rarely any variation within utility), and thus a stated preference approach is valuable to understand how attributes affect enrollment.

The main focus of the survey was the TOU choice tasks. There were two versions of the survey that varied only in the number of TOU plans presented in each choice task. The "simple" version presented only one TOU plan, and the "multiple" version presented two TOU plans. Each choice task presented asked respondents to choose between the given TOU plan(s) and a flat rate plan.[3] All respondents were shown three choice tasks, and we did not vary the number of plans presented within subject, but varied that between subjects for ease of understanding.

Each hypothetical TOU rate plan is defined by an off-peak price, an on-peak price, and hours of the day that are on-peak. The flat rate plan has the same price regardless of time of day. Figure 1 displays example choice sets for the simple version of the survey and the multiple version of the survey.

In order for the choices to make sense, the prices need to be grounded in reality. We used data from the 2019 EIA Form 861 to calculate the average per kwh rate for each state. Using respondents' state of residence, we match them to this state-specific approximate flat rate. For TOU prices, we gathered information on existing TOU plans from around the country and developed realistic ratios of off-peak to flat and on-peak to flat. We then extrapolated beyond the observed range to increase variance in the offerings. Finally, to estimate state-specific TOU plans, we multiply the flat rate by the ratios. For example, if the off-peak ratio was 0.8 and the flat rate price was $0.10/kwh, then the off-peak price would be $0.08/kwh. Table 1 lists the five sets of ratios used in our design.[4] Table 1 also lists the possible values that on-peak hours can take. In the three choice questions a respondent sees, we randomize which TOU price ratio and which set of on-peak hours are used for each plan. In the multiple version of the survey, we similarly randomize plan attributes, but constrain the randomization to not allow the two TOU plans to have the same price ratios.[5]

[3] While it is rare for utilities to offer multiple TOU plans, our far-from-exhaustive search of utilities' TOU plans uncovered two that offered multiple TOU plans for residential customers (Salt River Project in Phoenix and San Diego Gas and Electric). Salt River Project's two plans are different both in terms of on-peak hours and peak to off-peak price spread, which is similar to our experimental design.

[4] The range of price ratios is larger than the data we gathered from existing programs. We wanted to extend the range to understand if more disparity in those ratios impacted enrollment. By offering a large range of values, we can better estimate preferences for each attribute. An off-peak price of zero may seem extreme, however, it is feasible that a utility could charge a higher fixed cost to cover distribution and only charge positive marginal prices during peak times. This scenario becomes more likely as renewable energy increases penetration.

[5] We designed our survey such that price ratio and on-peak hours varied independently, so that we could separately identify preferences for those attributes. However, one concern about this design is that the implied average price

The survey has the following structure. The survey begins with screener questions for age and state of residence. Respondents must be at least 18 and must live in a state that does not have a high-level of TOU penetration (in order to minimize the odds that a respondent is already on a time-varying plan).[6] If either screener condition is not met, then the survey ends. If both conditions are met, the survey then presents information about TOU pricing including a diagram to understand changing rates over the course of a day. At that point, the survey presents the three TOU choice tasks. Lastly, the survey asks about the average monthly electric bill, general risk tolerance, and standard demographics. The complete survey instrument is available in the online appendix.

3.2 Survey implementation

We recruited online survey respondents using Amazon Mechanical Turk ("Mturk") between December 1 and December 22, 2020. Mturk has been validated as a recruitment tool by a variety of sources that found that, while Mturk workers are typically younger and more educated than the general population (Paolacci and Chandler 2014), they are largely representative of the general population across most psychological dimensions (Goodman and Paolacci 2017; McCredie and Morey 2019). We specifically recruited Mturk workers with greater than zero approved tasks, task approval rating greater than 90%, located in the United States, and had not completed the survey previously. Only Mturk workers that fit the initial screening criteria saw the announcement for a "6-Minute Academic Survey on Energy". If workers chose to accept the task, they clicked on a link to the Qualtrics survey. Respondents were compensated $1 upon completion of the survey. In addition to the MTurk and screener criteria, we used methods developed by Winter et al. (2019) to disallow respondents that were attempting to take the survey from outside the United States or if their IP address was associated with a known server farm.

Due to Qualtrics coding complexity, we created two versions of the survey, one for the simple version (with only one TOU plan offered per choice task) and one for the multiple version (with two TOU plans offered per choice task). To ensure that no respondent took both versions of the survey, we conducted the surveys sequentially on MTurk, with the simple version conducted December 1 to December 11 and the multiple version conducted December 14 to December 22. Because respondents were not randomized into the simple and multiple versions, this raises the concern that there could be respondent differences across the two samples. Intuitively, we are not worried because the pool of eligible workers is much larger than our

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per kwh will be very different across different TOU plans. It is possible that respondents will make choices based on average price instead of the TOU plan characteristics presented in the choice task. Because average price is mechanically related to TOU price ratios, on-peak duration, and flat rate, it is inappropriate to include this variable in our mdoel because the standard "all else equal" assumption of multiple regression would not hold. Exploring the importance of average price versus price spread would be a valuable area for future research.

[6] Using EIA Form 861 data, we calculate the proportion of customers in some kind of time-varying rate. We exclude nine states with greater than 5% enrollment, which are Arizona, Arkansas, California, Delaware, Illinois, Louisiana, Maryland, Montana, Ohio, and Oklahoma. Additionally, we excluded respondents from Alaska and Hawaii due to possible disparities in those states to the conterminous US.

sample size, implying we are not drawing on a different kind of worker for the second sample, and the timing of the surveys is quite similar, meaning there are no seasonal differences in the types of workers participating. However, we empirically compare respondent characteristics and find a high degree of similarity.[7] Thus, while not truly randomized, we argue that our two samples are as good as random.

3.3 Sample data and variable definitions

We collected data from 792 respondents across 38 states. The mean time to complete the survey was 6.15 minutes. We exclude respondents who took fewer than two minutes (21.9%) because at that time they are unlikely to be engaging in the material. We also exclude respondents who reported not knowing their electricity bill (0.9%). After those exclusions, we have 592 respondents, which combine for a total of 1,776 TOU enrollment choice tasks.

Table 2 presents summary statistics for our sample. In all of our empirical models, TOU enrollment will be our dependent variable. In our sample, respondents chose to enroll in TOU in 42.3% of choice tasks. This is substantially higher than is observed in real-world voluntary enrollment setting, which likely reflects the hypothetical nature of the choice (Nicolson et al. 2018). However, the focus of our analysis is comparing enrollment decisions across situations and not to predict real-world enrollment, so this level is not concerning.[8] 48.5% of respondents take the multiple version of the survey. Risk tolerance is self-assessed; respondents rated themselves on a scale from zero to 10 about how willing they are to take risks. The average in our sample is 5.7, with an observed minimum of zero and maximum of 10.[9] Respondents currently pay an average flat rate of 13.2 cents/kwh for electricity and have an average monthly electricity bill of $113.80. About 56% are homeowners, 43% affiliate with the Democratic Party and 33% affiliate with the Republican Party. The sample is relatively young, skews male, and is well educated. The average household income is $60,100, and 52% have a child living at home with them.[10]

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[7] Table A1 in the online appendix compares means across samples for the variables risk tolerance, current flat rate, monthly electricity bill, and eight demographic characteristics. All variables are stistically equivalent across samples, except for current flat rate, which is 0.4 cents/kwh lower in the multiple sample, and that difference is statistically significant at the 10% level. However, Figure A1 plots the density of current flat rate across the two samples, and the two distributions are quite similar and have strong overlap.

[8] In addition, respondents' decisions analyzed in our sample likely reflect their intentions to enroll or not enroll in a TOU plan. The intention to enroll is a precondition for the actual enrollment so our results have important implications for influencing consumers' relevant intentions which will then lead to the actions.

[9] Figure A2 in the online appendix presents a histogram of risk tolerance. There is considerable variation in risk tolerance, with the full range of values present and a seemingly a bi-modal distribution, with respective peaks at two and eight.

[10] In Table A2 in the online appendix, we examine how our survey population compares to the general population, as measured by the 2021 American Community Survey. We find that our survey respondents skew younger, male, and lower income. Large discrepancies exist in terms of college education and having children at home. These types of differences are common when using MTurk (Fisman et al. 2020). While our survey experiment uses randomization and hence results should be robust to changes in the sample, it is important to verify this. In Tables A3-A5, we estimate the same models presented in Tables 3-5 except applying sampling weights so that sample means match the general population in terms of being college educated and having a child. We focus on those two characteristics because those are where our sample means and ACS means differ most, following Fisman et al.

4. Results

We organize the presentation of our results around three research questions, which we address sequentially through different models and subsets of data.

Research Question 1: *Do TOU plan characteristics impact voluntary enrollment when only one TOU plan is offered?*

This research question seeks to answer whether TOU plan price sreads and peak-hour timing matter for enrollment. This is the standard context of one plan being offered. Most utilities and all prior field or survey experiments only offer one plan when enrolling customers. We estimate the following model:

(1)
$$Enroll_{ic} = \beta_1 OffPeakRatio_{ic} + \beta_2 OnPeakStartTime_{ic} + \beta_3 OnPeakLength_{ic} + \boldsymbol{X_i \gamma} + \varepsilon_{ic}$$

where subscript *i* indicates individual person; subscript *c* indicates the choice task and each person was shown three choice tasks; $Enroll_{ic}$ is a dummy variable equal to 1 if person *i* chooses the TOU plan in choice task *c* and equal to 0 if they choose the flat rate option. $OffPeakRatio_{ic}$ is the ratio between the off-peak price and flat rate price; $OnPeakStartTime_{ic}$ is the starting time of the on-peak hours and takes the values of 12, 14, 15, 16, or 17 (hour of day) in our data; $OnPeakLength_{ic}$ is the hours of on-peak duration and takes the values of 3, 5, or 8. These three variables represent all attributes of the TOU plan.[11] β_1, β_2, and β_3 are the coefficients of interest. We hypothesize that $\beta_1 > 0$ because people would be more likely to enroll if the price spread between off-peak and on-peak is smaller because that means less uncertainty. However, it is possible that $\beta_1 < 0$ if people are confident in their ability to load-shift and reduce their energy bill. If $\beta_1 = 0$, then people's decision to enroll is not impacted by the price spread. We do not have a hypothesis about β_2; it may be the case that an earlier start time is better for some, but a later start time is better for others, but no clear direction at the population level. We hypothesize that $\beta_3 < 0$ because less time on-peak makes it easier to load-shift and increases the opportunity to save money. While the TOU plan attributes are randomized and hence should not be meaningfully correlated with respondent characteristics, our model includes a comprehensive set of control variables that may influence enrollment decisions in order to eliminate any potential confounding impacts and improve model fit. $\boldsymbol{X_i}$ is a vector of consumer-specific characteristics including risk tolerance, monthly electricity bill, whether the person is a homeowner, political affiliation (Democrat, Republican, other), age, gender, household income, whether the person is college-educated, and whether there is any child at

(2020), who also use MTurk survey data. Results using weights are very similar to not using weights, suggesting findings are generalizable. Still, future research seeking to replicate these findings using a more representative sample would be beneficial.

[11] We cannot include both $OffPeakRatio$ and $OnPeakRatio$ in the same model because they are collinear. As a result, the coefficient on $OffPeakRatio$ should be interpreted as the joint impact of these two variables, which is the degree of price spread in the plan. If we include $OnPeakRatio$ instead of $OffPeakRatio$, our conclusions are identical, even though the coefficient on $OnPeakRatio$ is the opposite sign as the coefficient on $OffPeakRatio$.

home. We include census division fixed effects to control for regional-specific characteristics. We estimate this model using a linear probability model (LPM) on the sample of respondents who are given the simple version of the survey.[12] There is one observation per choice task.

Results in Table 3 show that when only one TOU plan is presented to the consumers, the coefficients of off-peak ratio and on-peak start time are not statistically significant, while the coefficient of on-peak length is negative and statistically significant. This indicates that when only one TOU plan is available to choose from, consumers only pay attention to the on-peak length while lacking attention to prices. The longer the on-peak hours, the more electricity consumption behavioral changes are needed in order to avoid the higher priced on-peak hours. In particular, when the on-peak length increases by 1 hour, the probability of enrolling in the TOU plan decreases by 2.5 percentage points (a 5.9% drop compared to the average enrollment rate of 42.3%). The lack of attention to the price ratio is related to the energy cost inattention issue as discussed in the introduction. Such inattention is also related to inelastic price elasticity of demand for electricity in the short-run as estimated by existing literature (Ito 2014; Burke and Abayasekara 2018).

In terms of consumer-specific characteristics, risk tolerance has a statistically significant impact on TOU enrollment. More risk-seeking consumers are more likely to enroll, which is consistent with Qiu, Colson, and Wetzstein 2017. Given the uncertainty of the electricity consumption patterns, enrolling in a TOU can potentially increase electricity bills if consumers fail to shift a sufficient amount of electricity consumption from on-peak hours to off-peak hours. As a result, risk-averse consumers are less likely to enroll in a given TOU plan. Based on our result, when the scale of risk preference increases by 1 (1 unit more risk-seeking), the probability of enrollment increases by 4.5 percentage points (a 10.6% increase compared to the average). Given the observed range of risk tolerance (11 point spread), the most risk tolerant respondent is expected to be 45 percentage points more likely to enroll than the most risk averse respondent. Clearly, risk tolerance is a critical determinant of TOU enrollment, though one that cannot be impacted by a utility's plan offerings.

Monthly electricity bill, age, female, and child at home are also factors that have a statistically significant impact on TOU enrollment. When the electricity bill and the age of the respondent increase, the enrollment probability drops. This could be due to the fact that it is more difficult for households with higher electricity bills and older people to shift electricity consumption from peak hours to off-peak hours. Female respondents are more likely to enroll, possibly because females pay more attentive to household expenditure and costs (Lee, Park, and Han 2013). Households with a child at home are more likely to enroll, possibly because adults with children pay more attention to the environment and they care more about the welfare of the next generation (Dupont 2004) or because children and what they learn at school can influence energy decisions (Gill and Lang 2018), but this is speculative.

[12] We use the linear probability model in order to directly interpret the coefficients as the marginal impact on the probability of enrolling. Results using a logit model are near identical and available from the authors by request.

Research Question 2: *Are people more likely to enroll in TOU if offered more than one plan?*

The previous research question is in a standard context of one plan being offered. Research Question 2 adds another context where each participant is offered more than one TOU plan. We seek to answer whether offering more than one TOU plan can increase the TOU enrollment probability. We develop a regression model that compares enrollment propensity for those offered multiple TOU plans to those offered only one TOU plan, while controlling for possible individual-level confounding factors:

(2) $$EnrollRate_i = \beta_1 Multiple_i + \boldsymbol{X_i \gamma} + \varepsilon_i$$

where $EnrollRate_i$ is the rate at which person *i* chooses a TOU plan among all three choice tasks presented, and so this variable can take on values 0, 0.33, 0.67, and 1. $Multiple_i$ is an indicator variable equal to one if the respondent took the version of the survey with multiple TOU plans offered in a single choice set and equal to zero if only one TOU plan was offered in each choice set. β_1 is the coefficient of interest. We hypothesize that $\beta_1 > 0$ because the ability to compare across different TOU plans can potentially change consumers' valuations of each TOU plan and increase the probability of adopting the relatively more attractive plan among the TOU options offered. Because survey version is effectively random, we do not expect confounding factos to influence estimates. However, we include the same set of control variables, $\boldsymbol{X_i}$, as defined with in Equation (1), in order to eliminate any potential confounding impacts and improve model fit. We estimate this model using ordinary least squares (OLS) using both samples of respondents who are given the simple version and multiple versions of the survey. There is one observation per respondent.

Table 4 shows that when multiple TOU plans are presented to people instead of offering only one TOU plan, the likelihood of TOU enrollment will increase by 14.2 percentage points (a 33.5% increase compared to the average enrollment rate). As discussed earlier, we hypothesize this results is explained by the decoy effect (Huber et al. 1982, Ariely and Wallsten 1995). When two TOU price plans are presented to the consumers, their valuations of individual price plans or their attributes could change due to the presence of another plan: the relatively less attractive TOU plan (i.e. those with longer on-peak hours) will make consumers' valuations of the relatively more attractive plan higher, thus potentially increasing the likelihood of choosing to enroll in one of the TOU plans. In Table 4, the coefficient of risk tolerance stays positive and statistically significant.

Research Question 3: *Do TOU plan characteristics impact voluntary enrollment when multiple TOU plans are offered?*

Having established that offering multiple TOU plans substantially increases enrollment, we now seek to understand why. What are the mechanisms leading to increased enrollment and are the characteristics of TOU plans part of that story? We develop a regression model that examines how enrollment decisions change based on a given plan's TOU characteristics as well as the alternative plan's TOU characteristics, while controlling for possible individual-level confounding factors:

$$(3) \quad Enroll_{ic} = \beta_1 OffPeakRatio_{ic} + \beta_2 OnPeakStartTime_{ic} \\ +\beta_3 OnPeakLength_{ic} + \beta_4 AltnerativeOffPeakRatio_{ic} \\ +\beta_5 AltnerativeOnPeakStartTime_{ic} \\ +\beta_6 AltnerativeOnPeakLength_{ic} + \boldsymbol{X_i\gamma} + \varepsilon_{ic}$$

We estimate this model using only the sample of respondents who are given the multiple version of the survey. We build the data such that each decision about a TOU plan is an observation, meaning that each choice task yields two observations. In Equation 3, $Enroll_{ic}$, $OffPeakRatio_{ic}$, $OnPeakStartTime_{ic}$, $OnPeakLength_{ic}$, and $\boldsymbol{X_i}$ have the same definitions as in Equation (1) and are the characteristics of the TOU plan of which the enrollment status is analyzed. $AltnerativeOffPeakRatio_{ic}$, $AltnerativeOnPeakStartTime_{ic}$, and $AltnerativeOnPeakLength_{ic}$ are the off-peak ratio, on-peak start time, and on-peak length of the other TOU plan that is presented in the choice task. For example, referring the Multiple TOU choice portion of Figure 1, for the observation focused on whether Plan 1 was chosen, $OffPeakRatio$ would equal 0.9, $OnPeakStartTime$ would equal 12, $OnPeakLength$ would equal 8, $AltnerativeOffPeakRatio$ would equal 0.3, $AltnerativeOnPeakStartTime$ would equal 16, and $AltnerativeOnPeakLength$ would equal 5. Because plan characteristics are independently paired, we can separately identify the effects of both an offered plan and an alternative plan.

While the coefficient on $OffPeakRatio$ is found to be statistically insignificant in Equation (1) using only the simple survey sample, in Equation (3), we hypothesize that price ratios will be meaningful. Our intuition is that when multiple TOU plans are offered, consumers can make comparisons on the TOU margin, instead of just the binary TOU versus flat rate. Therefore, we hypothesize that β_1 and β_4 in Equation (3) will be statistically significant and have the opposite signs, though we have no a priori intuition about which will be positive and which will be negative.

Results are presented in Table 5. The first column includes only TOU plan characteristics for the plan of which the enrollment status is analyzed, and the second column adds TOU plan characteristics for the alternative plan being offered. Across both columns, the coefficient on $OffPeakRatio$ is negative and statistically significant, and over 10 times the magnitude of the corresponding coefficient in Table 3. The negative sign indicates that when the off-peak ratio is larger (when the spread between the off-peak and on-peak electricity prices is smaller), the enrollment probability drops, and hence, people prefer a larger price spread. In Column (2), the coefficient on $AltnerativeOffPeakRatio$ is positive and statistically significant. This implies that when the price spread between the off- and on-peak periods of the alternative plan is smaller, consumers find the alternative plan less attractive and are more likely to enroll in the original TOU plan. Again, this finding is consistent with a preference for larger price spreads between off- and on-peak. These findings suggest that a utility can maximize voluntary enrollment by maximizing dissimilarity of the prices of competing TOU plans. For example, consider the price ratios used in our experiment shown in Table 1, presented as (ratio of off-peak price to flat rate, ratio of on-peak price to flat rate). If two TOU plans are offered with off-peak and on-peak price ratios of (0, 10) and (0.9, 1.8), this coupled offer will increase enrollment by 7.1 percentage points relative to an offer of two TOU plans with price ratios of (0.8, 2.7) and (0.9, 1.8). This may suggest that consumers' motivations to enroll in a TOU plan are on average financially driven. When the off-peak ratio is small (large price spread), consumers can save more on their energy bills by shifting electricity consumption from on-peak to off-peak hours. It is perhaps the prospect to save that increases their likelihood of enrolling.

Similar to the results in Table 3, on-peak length and risk tolerance remain statistically significant in influencing the TOU enrollment decision. However, on-peak length of the alternative plan does not influence enrollment. Hence we only find evidence that respondents are making plan comparisons based on price, and that this is the most likely mechanism that leads to increased enrollment when multiple plans are offered.

As discussed previously, we interpret our findings as consistent with the decoy effect. When another TOU plan is present, that plan can act as a reference point from which consumers can compare across plans and pay more attention to the attributes of the TOU plans. Our results also offer evidence that price only sometimes matters. TOU pricing, and time-varying pricing in general, is motivated by our understanding that people respond to price signals. Of course, this is once they are already enrolled. What we find is that price can also be a determinant for enrolling, but only if multiple plans are offered.

5. Conclusion and Policy Implications

We design and conduct a survey aimed at understanding factors that utilities can leverage to increase voluntary enrollment in TOU electricity pricing plans. Our results show that consumers will be more likely to enroll if offered more than one plan. The mechanism to explain this phenomenon is that when multiple TOU plans are present, consumers become attentive to the price ratios of the TOU plans and compare them to assess financial pros and cons of enrolling. We find that consumers are more likely to choose the plan that has a larger price spread between the off- and on-peak hours. If the goal is to increase the TOU enrollment, the implication of our results to the utilities and policymakers is that 1) more than one TOU plan should be offered to the consumers and 2) the disparity between price ratios should be maximized.

When more than one TOU plan is offered, the key factors that impact enrollment decisions are off-peak ratio, on-peak length, and consumers' risk tolerance. These findings have important implications for increasing TOU enrollment. A TOU plan with a larger price spread can potentially increase the enrollment rate if consumers believe they can successfully shift their consumption behaviors and save money. A TOU plan with a smaller on-peak length can lower the cost of electricity behavioral changes and give consumers more flexibility of electricity consumption patterns, and thus can also increase the enrollment rate. Risk averse consumers are less likely to enroll in a TOU plan. While it is hard to change the risk preferences of consumers, utilities and policymakers can reduce the perceived risk levels of the TOU plans. Since TOU is a relatively new pricing scheme for consumers, studies show that the perceived risk level of new energy programs or technologies can be higher than the actual risk level (Qiu, Colson, and Grebitus 2014; Qiu, Wang, and Wang 2015; Sutherland 1991; Howarth and Sanstad 1995). Informational programs that provide more information about the TOU plans and tips about saving money from TOU can be helpful to reduce the perceived risk level and increase the enrollment rate.

When only one TOU plan is offered, our results show that consumers are not paying attention to the price ratio between off-peak price and flat price. This indicates that consumers might be inattentive to this price attribute, as supported by some existing studies which have found evidence of inattention to energy costs (Gerarden, Newell, and Stavins 2015). Such inattention could lead to sub-optimal decisions because some consumers can forego the opportunities to save on their electricity bills from enrolling in a TOU plan. One might argue that such inattention might be due to the time and cognitive costs needed to calculate the energy savings from a TOU price. However, given that we show when two TOU plans are offered, consumers do have the ability to respond to TOU price ratios, such inattention would then be most likely only due to lack of attention instead of cognitive constraints. Utilities could take these results in two directions. First, if enrollment is unresponsive to price spread, then a utility can set a price spread focusing only on demand response, without worrying about impacting enrollment. Second, utilities could offer an informational program to increase consumers' attention to the price attributes in an attempt to increase enrollment.

So far our discussion is centered around increasing the TOU enrollment given the very low enrollment of voluntary TOU plans currently and the potential social benefits of TOU. We acknowledge that an adverse selection problem exists where the consumers that do not consume much electricity during the peak hours in the first place tend to enroll in a voluntary TOU plan, thus saving on their electricity bills without needing to adjusting their electricity consumption patterns. In such a case, increasing TOU enrollment could initially dampen the benefits to the utilities if the majority of those who enroll are free-riders. However, the adverse selection problem and the optimal designs of the TOU attributes that can maximize social benefits are beyond the scope of our study. Assuming that the TOU plan is welfare-enhancing if all consumers are enrolled, then our results will be helpful for policymakers and utilities to increase the enrollment.

Future research can build on our findings. First, TOU rates are just one type of time-varying electricity rate. Similar surveys could be done examining preferences for critical peak pricing or rebates because 1) it is important to assess if our findings are generalizable to other rate types and 2) utilities may (or may not) be drawn to using these plans instead of TOU. Second, given concerns about hypothetical bias in our survey, ideally a field experiment could be executed with real enrollment decisions. Short of that, perhaps conducting a similar survey experiment, but with real utility customers with knowledge of their consumption patterns. Lastly, the findings of conditional price responsiveness could be examined in other areas, particularly settings with known energy inattention, such as appliance choice.

References

Allcott, Hunt. 2011. "Rethinking Real-Time Electricity Pricing." *Resource and Energy Economics*, Special section: Sustainable Resource Use and Economic Dynamics, 33 (4): 820–42. https://doi.org/10.1016/j.reseneeco.2011.06.003.

Andor, Mark A., Andreas Gerster, and Stephan Sommer. 2020. "Consumer Inattention, Heuristic Thinking and the Role of Energy Labels." *The Energy Journal* 41 (1). https://doi.org/10.5547/01956574.41.1.mand.

Ariely, D., & Wallsten, T. S. (1995). Seeking subjective dominance in multidimensional space: An explanation of the asymmetric dominance effect. *Organizational Behavior and Human Decision Processes*, *63*(3), 223-232.

Belton, Cameron A., and Peter D. Lunn. 2020. "Smart Choices? An Experimental Study of Smart Meters and Time-of-Use Tariffs in Ireland." *Energy Policy* 140 (May): 111243. https://doi.org/10.1016/j.enpol.2020.111243.

Borenstein, Severin, and Stephen Holland. 2005. "On the Efficiency of Competitive Electricity Markets with Time-Invariant Retail Prices." *The RAND Journal of Economics* 36 (3): 469–93.

Burke, Paul J., and Ashani Abayasekara. 2018. "The Price Elasticity of Electricity Demand in the United States: A Three-Dimensional Analysis." *The Energy Journal* 39 (2). https://doi.org/10.5547/01956574.39.2.pbur.

Choi, Dong Gu, Michael K. Lim, Karthik Murali, and Valerie M. Thomas. 2020. "Why Have Voluntary Time-of-Use Tariffs Fallen Short in the Residential Sector?" *Production and Operations Management* 29 (3): 617–42. https://doi.org/10.1111/poms.13126.

Diamond, Peter A., and Jerry A. Hausman. 1994. Contingent valuation: is some number better than no number?. *Journal of economic perspectives*, *8*(4), pp.45-64.

Di Cosmo, Valeria, Sean Lyons, and Anne Nolan. 2014. "Estimating the Impact of Time-of-Use Pricing on Irish Electricity Demand." *The Energy Journal* 35 (2). https://doi.org/10.5547/01956574.35.2.6.

Dupont, Diane P. 2004. "Do Children Matter? An Examination of Gender Differences in Environmental Valuation." *Ecological Economics* 49 (3): 273–86.

Eisenack, Klaus, and Mathias Mier. 2019. "Peak-Load Pricing with Different Types of Dispatchability." *Journal of Regulatory Economics* 56 (2): 105–24. https://doi.org/10.1007/s11149-019-09394-9.

Faruqui, Ahmad, and Sanem Sergici. 2010. "Household Response to Dynamic Pricing of Electricity: A Survey of 15 Experiments." *Journal of Regulatory Economics* 38 (2): 193–225. https://doi.org/10.1007/s11149-010-9127-y.

Fisman, R., Gladstone, K., Kuziemko, I., & Naidu, S. (2020). Do Americans want to tax wealth? Evidence from online surveys. *Journal of Public Economics*, 188, 104207.

Fowlie, Meredith, Catherine Wolfram, C. Anna Spurlock, Annika Todd, Patrick Baylis, and Peter Cappers. 2021. "Default Effects and Follow-On Behavior: Evidence from an Electricity Pricing Program." *The Review of Economic Studies* 88 (6): 2886-2934. https://doi.org/10.1093/restud/rdab018.

Gerarden, Todd, Richard G. Newell, and Robert N. Stavins. 2015. "Deconstructing the Energy-Efficiency Gap: Conceptual Frameworks and Evidence." *American Economic Review* 105 (5): 183–86. https://doi.org/10.1257/aer.p20151012.

Gill, Carrie and Corey Lang. 2018. Learn to conserve: The effects of in-school energy education on at-home electricity consumption. *Energy Policy*, *118*, pp.88-96.

Goodman, Joseph K, and Gabriele Paolacci. 2017. "Crowdsourcing Consumer Research." *Journal of Consumer Research* 44 (1): 196–210. https://doi.org/10.1093/jcr/ucx047.

Holland, Stephen P., and Erin T. Mansur. 2008. "Is Real-Time Pricing Green? The Environmental Impacts of Electricity Demand Variance." *The Review of Economics and Statistics* 90 (3): 550–61. https://doi.org/10.1162/rest.90.3.550.

Howarth, Richard B., and Alan H. Sanstad. 1995. "Discount Rates and Energy Efficiency." *Contemporary Economic Policy* 13 (3): 101–9. https://doi.org/10.1111/j.1465-7287.1995.tb00726.x.

Huber, J., Payne, J. W., & Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of consumer research*, *9*(1), 90-98.

Ito, Koichiro. 2014. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." *American Economic Review* 104 (2): 537–63. https://doi.org/10.1257/aer.104.2.537.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka. 2021. "Selection on Welfare Gains: Experimental Evidence from Electricity Plan Choice." w28413. National Bureau of Economic Research. https://doi.org/10.3386/w28413.

Jessoe, Katrina, David Rapson, and Jeremy B. Smith. 2014. "Towards Understanding the Role of Price in Residential Electricity Choices: Evidence from a Natural Experiment." *Journal of Economic Behavior & Organization* 107 (November): 191–208. https://doi.org/10.1016/j.jebo.2014.03.009.

Johnson, E.J., & Goldstein, D. (2003). Do Defaults Save Lives? *Science, 302(5649),* 1338-1339.

Johnston, Robert J., Kevin J. Boyle, Wiktor Adamowicz, Jeff Bennett, Roy Brouwer, Trudy Ann Cameron, W. Michael Hanemann et al. 2017. Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists*, *4*(2), pp.319-405.

Kahneman, D., Knetsch, J.L., & Thaler, R.H. (1990). Experimental tests of the endowment effect and the Coase theorem. *Journal of Political Economy*, *98(6),* 1325-1348.

Lang, C., Weir, M., & Pearson-Merkowitz, S. (2021). Status quo bias and public policy: evidence in the context of carbon mitigation. *Environmental Research Letters*, *16*(5), 054076.

Lee, Eunsil, Nam-Kyu Park, and Ju Hyoung Han. 2013. "Gender Difference in Environmental Attitude and Behaviors in Adoption of Energy-Efficient Lighting at Home." *Journal of Sustainable Development* 6 (9): 36.

McCredie, Morgan N., and Leslie C. Morey. 2019. "Who Are the Turkers? A Characterization of MTurk Workers Using the Personality Assessment Inventory." *Assessment* 26 (5): 759–66. https://doi.org/10.1177/1073191118760709.

Mostafa Baladi, S., Joseph A. Herriges, and Thomas J. Sweeney. 1998. "Residential Response to Voluntary Time-of-Use Electricity Rates." *Resource and Energy Economics* 20 (3): 225–44. https://doi.org/10.1016/S0928-7655(97)00025-0.

Nicolson, Moira L., Michael J. Fell, and Gesche M. Huebner. 2018. "Consumer Demand for Time of Use Electricity Tariffs: A Systematized Review of the Empirical Evidence." *Renewable and Sustainable Energy Reviews* 97 (December): 276–89. https://doi.org/10.1016/j.rser.2018.08.040.

Palmer, Karen, and Margaret Walls. 2015. "Limited Attention and the Residential Energy Efficiency Gap." *American Economic Review* 105 (5): 192–95. https://doi.org/10.1257/aer.p20151009.

Paolacci, Gabriele, and Jesse Chandler. 2014. "Inside the Turk: Understanding Mechanical Turk as a Participant Pool." *Current Directions in Psychological Science* 23 (3): 184–88. https://doi.org/10.1177/0963721414531598.

Parrish, Denise. 2013. "Time of Use Tariffs: Examples from the U.S." Presented at the Presentation at the ERRA Tarff/Pricing Committee, Abu Dhabi, U.A.E. 6-7 February 2013.

Poe, G.L. (2016). Behavioral anomalies in contingent values and actual choices. *Agricultural and Resource Economics Review*, *45(2)*, 246-269.

Prest, B. C. (2020). Peaking interest: How awareness drives the effectiveness of time-of-use electricity pricing. *Journal of the Association of Environmental and Resource Economists*, *7*(1), 103-143.

Qiu, Yueming, Gregory Colson, and Carola Grebitus. 2014. "Risk Preferences and Purchase of Energy-Efficient Technologies in the Residential Sector." *Ecological Economics* 107 (November): 216–29. https://doi.org/10.1016/j.ecolecon.2014.09.002.

Qiu, Yueming, Gregory Colson, and Michael E. Wetzstein. 2017. "Risk Preference and Adverse Selection for Participation in Time-of-Use Electricity Pricing Programs." *Resource and Energy Economics* 47: 126–42.

Qiu, Yueming, Loren Kirkeide, and Yi David Wang. 2018. "Effects of Voluntary Time-of-Use Pricing on Summer Electricity Usage of Business Customers." *Environmental and Resource Economics* 69 (2): 417–40.

Qiu, Yueming, Yi Wang, and Jianfeng Wang. 2015. "Implied Discount Rate and Payback Threshold of Energy Efficiency Investment in the Industrial Sector." *Applied Economics*.

Schittekatte, T., Mallapragada, D. S., Joskow, P. L., & Schmalensee, R. (2022). Electricity Retail Rate Design in a Decarbonized Economy: An Analysis of Time-Of-Use and Critical Peak Pricing (No. w30560). National Bureau of Economic Research.

Schleich, Joachim, Corinne Faure, and Xavier Gassmann. 2019. "Household Internal and External Electricity Contract Switching in EU Countries." *Applied Economics* 51 (1): 103–16. https://doi.org/10.1080/00036846.2018.1494379.

Smith, S. M., & Krajbich, I. (2019). Gaze amplifies value in decision making. *Psychological science*, *30*(1), 116-128.

Steiner, Peter O. 1957. "Peak Loads and Efficient Pricing." *The Quarterly Journal of Economics* 71 (4): 585–610. https://doi.org/10.2307/1885712.

Sutherland, Ronald J. 1991. "Market Barriers to Energy-Efficiency Investments." *The Energy Journal* 12 (3). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol12-No3-3.

Thaler, R.H. & Benartzi, S. (2004). Save More TomorrowTM: Using Behavioral Economics to Increase Employee Saving. *Journal of Political Economy*, *112(1)*, 164–87.

Towal, R. B., Mormann, M., & Koch, C. (2013). Simultaneous modeling of visual saliency and value computation improves predictions of economic choice. *Proceedings of the National Academy of Sciences*, *110*(40), E3858-E3867.

Williamson, Oliver E. 1966. "Peak-Load Pricing and Optimal Capacity under Indivisibility Constraints." *The American Economic Review* 56 (4): 810–27.

Winter, Nicholas, Tyler Burleigh, Ryan Kennedy, and Scott Clifford. 2019. "A Simplified Protocol to Screen Out VPS and International Respondents Using Qualtrics." SSRN Scholarly Paper ID 3327274. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.3327274.

Wolak, Frank A. 2011. "Do Residential Customers Respond to Hourly Prices? Evidence from a Dynamic Pricing Experiment." *American Economic Review* 101 (3): 83–87. https://doi.org/10.1257/aer.101.3.83.

Ziegler, Andreas. 2020. "Heterogeneous Preferences and the Individual Change to Alternative Electricity Contracts." *Energy Economics* 91 (September): 104889. https://doi.org/10.1016/j.eneco.2020.104889.

Figures and Tables

Figure 1: Illustration of TOU enrollment choice questions

Simple TOU choice:

	Plan 1	Plan 2
Off-peak price	\$0.09	\$0.10
On-peak price	\$0.18	\$0.10
On-peak hours (M-F only)	Noon-8pm	NA

Multiple TOU choice:

	Plan 1	Plan 2	Plan 3
Off-peak price	\$0.09	\$0.03	\$0.10
On-peak price	\$0.18	\$0.70	\$0.10
On-peak hours (M-F only)	Noon-8pm	4-9pm	NA

Table 1: Attributes of TOU plan characteristics

Attribute	Levels
Off-peak and on-peak price ratios relative to flat rate	(0, 10), (0.3, 7), (0.65, 4), (0.8, 2.7), (0.9, 1.8)
On-peak duration	Noon-8pm, 2-7pm, 4-9pm, 2-10pm, 3-6pm, 5-8pm

Table 2: Sample means

Variable	Mean	Standard deviation
TOU enrollment rate (%)	42.3	39.4
Multiple (%)	48.5	50.0
Risk tolerance	5.7	2.8
Current flat rate (cents/kwh)	13.2	3.0
Monthly electricity bill	113.8	43.4
Homeowner (%)	55.9	49.7
Democrat (%)	43.2	49.6
Republican (%)	33.4	47.2
Independent (%)	23.3	42.3
Age (years)	38.4	12.2
Female (%)	39.9	49.0
Household income ($ thousands)	60.1	37.6
College educated (%)	72.8	44.5
Child at home (%)	52.0	50.0
Respondents	592	

Notes: All variables come from survey responses, with the exception of current flat rate, which is from EIA and determined by their state of residence.

Table 3: Determinants of TOU enrollment with single TOU option

Independent Variables	(1)
Off-peak ratio	0.006
	(0.044)
On-peak start time	-0.018
	(0.015)
On-peak length (hours)	-0.025**
	(0.011)
Current flat rate (cents/kwh)	0.011
	(0.014)
Risk tolerance	0.045***
	(0.007)
Monthly electricity bill ($)	-0.001**
	(0.000)
Homeowner (1=yes)	-0.009
	(0.035)
Democrat (1=yes)	0.064
	(0.047)
Republican (1=yes)	0.076
	(0.052)
Age (years)	-0.004**
	(0.001)
Female (1=yes)	0.078**
	(0.036)
Household income ($ thousands)	-0.000
	(0.001)
College educated (1=yes)	0.017
	(0.047)
Child at home (1=yes)	0.194***
	(0.038)
R-squared	0.203
Respondents	305
Choices	915

Notes: Dependent variable is TOU enrollment. Sample includes only respondents taking the version of the survey with a single TOU plan per choice set, and the level of observation is a choice set. Each model additionally includes question order dummies and Census division dummies. Standard errors are clustered at the respondent level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 4: The effect of multiple TOU plans on enrollment

Independent variables	(1)
Multiple (1=yes)	0.142***
	(0.028)
Risk tolerance	0.047***
	(0.005)
Current flat rate (cents/kwh)	0.010
	(0.011)
Monthly electricity bill ($)	-0.000
	(0.000)
R-squared	0.308
Respondents	592

Notes: TOU enrollment rate is the dependent variable. Sample includes all respondents, with one observation each. Each model additionally includes socioeconomic characteristics and Census division dummies. Robust standard errors are shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table 5: Determinants of TOU enrollment with multiple TOU options

Independent variables	(1)	(2)
Off-peak ratio	-0.083***	-0.089***
	(0.032)	(0.033)
On-peak start time	-0.009	-0.009
	(0.010)	(0.010)
On-peak length (hours)	-0.022***	-0.022***
	(0.008)	(0.008)
Alternative off-peak ratio		0.096***
		(0.031)
Alternative on-peak start time		-0.001
		(0.010)
Alternative on-peak length (hours)		0.001
		(0.008)
Current flat rate (cents/kwh)	0.003	0.003
	(0.009)	(0.009)
Risk tolerance	0.023***	0.023***
	(0.004)	(0.004)
Monthly electricity bill ($)	0.000	0.000
	(0.000)	(0.000)
R-squared	0.069	0.075
Respondents	287	287
Choice sets	861	861
TOU plan choices	1,722	1,722

Notes: Table presents two separate regression models, each with TOU enrollment as the dependent variable. Sample includes only respondents taking the version of the survey with multiple TOU plans per choice set, and the level of observation is a specific TOU plan on offer. Each model additionally includes socioeconomic characteristics, question order dummies, and Census division dummies. Standard errors are clustered at the respondent level and shown in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.