Pre-paid electricity plan and electricity consumption behavior [1]

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Abstract:

This paper demonstrates using basic economic theory that there are four possible channels via which a reduction in electricity consumption can be achieved by the adoption of a pre-paid plan: nudging, price effects, information provision, and costs of being disconnected. By using customer level residential billing data from 2008-2010 of a major utility company in Phoenix metropolitan area, this study adopts a matching approach and a difference-in-differences method to estimate empirically the impact of a pre-paid electricity plan on residential electricity consumption, after correcting for selection bias. Results show that the pre-paid program is associated with a 12% reduction in electricity usage, customers with lower level of wealth or those with higher amount of arrear prior to switching to the pre-paid program tend to save more electricity after switching, and pre-paid customers save more electricity in the summer than winter.

JEL: L94, Q41

Keywords: pre-paid electricity pricing, energy conservation, matching, difference-in-differences

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1. Introduction

Under the conventional method of paying for electricity bills (the post-pay scheme), a household pays for its electricity consumption once a month after they consume the electricity. This is quite different from the payment procedure for other consumption goods, such as groceries or gasoline, in which payment occurs prior to the consumption of the goods. One might wonder how would people's consumption for groceries or gasoline change if they pay for them once a month post consumption and/or only find out how much they have consumed when they pay for the monthly bills?

Similar to paying for consumption goods such as groceries, pre-paid electricity meters require customers to pay before consuming the electricity. In most cases, an in-home display usually accompanies the pre-paid system which provides feedback on how much energy or credit has been used. Currently there are only several utilities in Michigan, Arizona, Texas, Oklohama and Georgia that have pre-paid programs. Examples include Salt River Project (SRP) (pre-paid program beginning in 1993), Oklahoma Electric Cooperative (program starting in 2006), Public Utility Commission of Texas (program starting in 2011), and Detroit Edison pilot (program starting in 2010).

In 1993, SRP, a major utility company in Phoenix metropolitan area, started a pre-paid electricity program, commonly known as M-Power program. The M-Power program started out targeting only customers with arrears facing terminations in their services but was eventually made available to all customers for voluntary subscription. Through over two decades of technology and operation improvement, the M-Power program has grown to a mature program, with 16.4% of SRP's residential customers participating, making it the largest pre-paid program in the United States.

Assessing the impact of pre-paid electricity programs on electricity consumption is important in three aspects. First, the recent EPA's proposed rule on reducing carbon emissions from existing power plants identifies energy efficiency programs, including energy conservation programs, as one compliance mechanism (EPA, 2014). A pre-paid electricity program can be a candidate compliance program if there is adequate empirical evidence showing its energy conservation effects. Second, utility companies and other types of energy service companies have implemented various types of energy conservation, energy efficiency and demand side management programs and there have been rich number of studies examining these other types of programs. For example, studies find that home energy reports with information on households' own and peers' home electricity usage are effective at reducing households' energy consumption (Allcott, 2011b; Costa and Kahn, 2013). Utility rebates and financial incentives for energy conservation are also shown to have statistically significant impact on energy consumption (Ito, 2015). There are also studies evaluating utility dynamic electricity pricing programs such as real-time pricing and time-of-use pricing (Aigner et al., 1994; Wolak, 2011; Jessoe and Rapson, 2014; Jessoe et al., 2014; Qiu and Kirkeide, 2014). However, literature examining the impact of pre-paid electricity pricing programs on electricity consumption behavior has been rare. Third, the number of studies evaluating the impact of information provision programs through smart grid and in-home displays (IHDs) on consumers' electricity consumption has increased in recent years (Matsukawa, 2004; Hargreaves et al., 2010; Faruqui et al., 2010). Pre-paid electricity programs are closely related to such information provision programs because rich information such as electricity prices, real time consumption and expected consumption is usually provided to pre-paid electricity customers, hence it is essential to understand whether observed reduction in consumption (if any) is driven by timely information or from the payment procedure.

Though there is lack of empirical studies that quantitatively estimate the casual impact of pre-paid energy programs on consumer energy consumption, recently there has been an increase in the amount of qualitative studies focusing on customer and utility company satisfaction with pre-paid systems, with most of these studies focusing on overseas programs such as those in Europe, Africa and India. Anderson et al (2012) conduct a survey among 699 low-income households in Britain and find that one of the main benefits of pre-paid electricity program is that it gives customers better control of fuel costs and pre-paid customers are 2.6 times more likely to use energy rationally relative to others. Miyogo et al. (2013) survey pre-paid customers in Kenya and find that pre-paid customers are more careful about their energy consumption. O'Sullivan et al. (2014) conduct qualitative survey among several pre-paid meter customers in New Zealand and find that the pre-paid systems can help households better budget and manage their energy use though increased information feedback. On the other hand, consumers incur inconvenience to purchase the electricity every time when they need to charge their pre-paid card (in some of the systems consumers need to go to a Kiosk to charge their pre-paid card) as well as the worries and cost of being disconnected when the pre-paid card runs out (Tewari and Shah, 2003; O'Sullivan et al., 2014). The benefits of pre-paid systems to the utilities includes reduction of energy lost through theft resulted from illegal connections, reduction of fraud or non-payment of bills, and reduced financial risks from arrearage (Tewari and Shah, 2003; Bandyopadhyay, 2008; Khan et al., 2010; Ogujor and Otasowie, 2010; Mwaura, 2012). Casarin and Nicollier (2009) conduct a cost-benefit analysis of the adoption of pre-paid meters in a local community in Argentina and find that prepaid meters lead to an increase in welfare.

This paper first demonstrates using basic economic theory that there are four possible channels via which a pre-paid plan leads to electricity consumption reduction: nudging, price effects, information provision, and costs of being disconnected. Then, using customer level residential billing data from 2008-2010 obtained from SRP, this study adopts a matching approach and a difference-in-differences method to estimate empirically the impact of a pre-paid electricity plan on residential electricity consumption while correcting for selection bias. We find that the pre-paid program is associated with 12% reduction in electricity consumption. We also explore the heterogeneity in the response to pre-paid electricity pricing by wealth level. Using arrear amount as a proxy for wealth level, we find that customers with lower level of wealth tend to experience greater electricity reduction after the switch. In addition, results show that pre-paid customers save more electricity in the summer than winter, which has important implication for managing peak demand and load shape for utility companies since summer is when system peak demand usually happens.

The remainder of this paper is organized as following. Section 2 provides background to SRP's pre-paid electricity program. Section 3 presents the theoretical framework. Section 4 describes the empirical strategy and study design. Section 5 discusses the data. Section 6 contains econometric models and estimation results. Section 7 conducts robustness checks. Section 8 derives welfare and policy implications and Section 9 concludes.

2. SRP's pre-paid electricity program – M-Power program

SRP's pre-paid electricity program is commonly known as the M-Power program. When a customer initiates the M-power service, specific smart grid meter and User Display Terminals (UDT) will be installed at the customer's home. The customer will also be given the Smart

Cards which are unique to the customer's account. To add money to the Smart Card, customers need to go to a SRP PayCenter. By 2014, there are more than 110 PayCenters for the pre-paid card across SRP service territory. If the SmartCard runs out of money, the customer's electricity will be disconnected. Customers need to charge the Smart Card before it runs out of money in order to stay connected.

The UDT provides valuable information about a customer's energy consumption, including the current rate per hour displayed as dollars/hour based on the amount of electricity used in the previous hour, the rate charged displaying as a kWh rate, an estimate of today's electricity cost, yesterday's cost, estimated cost of the current month, cost of last month, an estimated number of days of service remaining with the current credit and the remaining credit (EPRI, 2010b). The UDT also gives warning signals when the customer's account balance is below $10.

SPR has conducted customer survey among its M-Power users. About 84 percent of customers reported that they are either ''very satisfied'' or ''satisfied' with the program. About 95 percent of customers reported that they have had better control of their electricity use.

3. Theoretical framework

The energy savings from a pre-paid program come from two distinct features of the program: information feedback from in-home displays (IHDs) and the prepay mechanism. Faruqui et al. (2010) finds that IHDs alone reduce energy consumption by about 7% while when combined with pre-paid mechanism, the amount of energy reduction is twice as much. Pre-pay with IHD versus post-pay options can influence consumers' electricity consumption behavior through four possible mechanisms: nudging, price effects, information provision, and costs of being disconnected. The directional impacts of these four mechanisms on electricity usage can be explained via simple models based on consumer theory.

If electricity is pre-paid, then it is similar to other consumption goods (e.g. food) that are pre-paid or pay-as-you-go. The consumer utility maximization problem for pre-paid electricity is then the standard one in the textbook.

Pre-paid scenario model set up:

Assume there are only two goods: x and y, where x is electricity; y is a composite of all other goods (spot transactions are assumed for y). Consumer's utility function is $u(x, y)$ with $u(x, y)$ being strictly increasing and concave in both goods. Price of x is p. Price of y is normalized to one. I is the disposable income. We also assume that the price of electricity is constant and known by consumers.

$$\max_{x,y} u(x, y) \qquad s.t. \quad px + y = I \quad and \;\; x \leq E$$

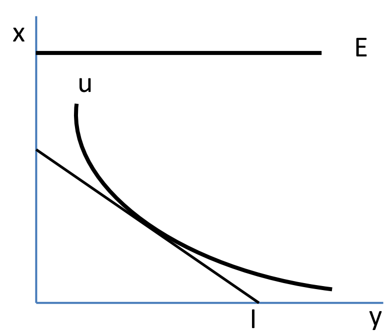

Figure 1. Utility maximization problem for pre-paid customers (without considering cost of pre-paid program)

The second constraint $x \leq E$ comes from the fact that electricity consumption is through household appliance stock. In the short run when the appliance stock is constant, households cannot consume electricty more than the capacity of the appliance stock. Figure 1 visualizes the utility maximization problem for pre-paid electricity customers.

3.1 Nudging on budgeting electricity consumption

The average monthly electricity bill in United States in 2012 is $107.28 (EIA, 2012). According to the 2012 consumer expenditure survey, average annual household expenditure is $51,442 in 2012(BLS, 2012), making electricity spending only 2.5% of total expenditure. Given that electricity spending is only a small portion of the overall household expenditure and the fact that conventionally electricity is post-paid on a monthly basis, households are less trained at tracking and budgeting their electricity expenditure (Smith, 2010; O'Sullivan et al., 2014) and customers sometimes over consume energy and experience “bill shock” (Anderson et al., 2012). This is also related to the “inattention” on energy costs as discussed in Allcott (2011a) and Allcott and Greenstone (2012).

Let’s assume an extreme case where the household completely forgets to budget its electricity expenditure, then the utility maximization problem becomes the following, assuming that households have some other means (e.g. through endowment) to cover for the electricity cost or incur arrearage when they receive that bill with a surprisingly high amount due.

$$\max_{x,y} u(x,y) \qquad s.t. \quad y = I \quad and \;\; x \leq E$$

The red lines in Figure 2 show the budget constraint and the utility maximization problem for such post-pay customers. The red utility curve intersects with the appliance stock constraint at x=E.

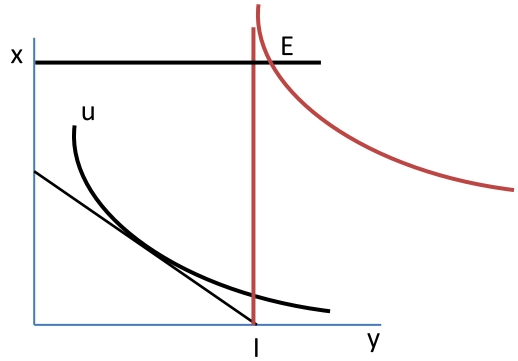

Figure 2. Utility maximization problem for post-pay customers
(ignoring budgeting electricity expenditure)

In this case consumers will consume more electricty (at the level of *E*) than the pre-paid case. Pre-paid scheme can nudge households to better budget electricity every month because consumers are more frequently reminded of the electricity expenditure and consumers need to pay before they can consume electricity.

3.2 Price effects

Now we assume that consumers do budget their electricity expenditure in a post-pay scheme. Because electricity payment occurs at the end of the period after consumption has already taken place, this expenditure will be discounted when households optimize their consumption problem.[5] Even though one month is relatively short and the relevant interest rate might be low, existing literature has shown evidence that people are present bias where they discount outcomes in near future more than for outcomes in the far future, which is referred to as hyperbolic discounting (Frederick et al., 2002). Assuming that the discount factor is β with $\beta<1$.

[5] Given that payment can be delayed to the end of the period in the post-pay scheme, any agent that discounts future cash flow would view deferred payment at today's price as a discount to the price.

$$\max_{x,y} u(x,y) \qquad s.t. \quad \beta px + y = I \quad and \;\; x \leq E$$

In a post-pay scheme, the price of electricty will be discounted and thus through both substitution and income effects, consumption of electricity will be increased. The tangent point of the red lines in Figure 3 indicates the solution to the utility maximization problem for post-pay customers who discount future cashflows. The new budget constraint is more steep and the new budget constraint is tangent to the the utility curve at a higher value of x.

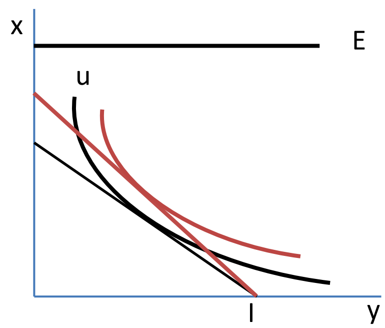

Figure 3. Utility maximization problem for post-pay customers (with discount factor)

The fact that pre-paid program should reduce consumption relative to post-paid scheme can also be viewed as who gets to enjoy the time value of money for the amount due on the electricity. In the post-paid scheme, the consumers enjoy it while pay-as-you-go transfers that surplus to the electricity providers. So although pay-as-you-go can be environmental friendly and enhance energy savings, it also has a negative impact to the consumers welfare as it in effect reduces their budget constraint and hence their individual utility.

3.3 Information provision

Again we assume that a household does budget its electricity consumption in a post-pay scheme. In a post-pay scheme, the household only finds out its consumption level after it has already consumed the electricity with a delay between consumption and bill arrival. In a pre-paid scheme, the household can monitor its electricity consumption in real time by reading the balance of its pre-paid meter. In addition, the inconvenience of being disconnected forces the household to pay more attention to electricity consumption as well as the remaining balance of its pre-paid meter (O'Sullivan et al., 2014). Thus in the pre-paid scheme, consumers can accurately budget their electricity consumption while in the post-pay scheme, consumers need to form an expectation (which can often deviate from realization) of their electricity consumption of the month.

Assume that the consumer-estimated amount of electricity consumption in the post-pay scheme is $\tilde{x}$ and $\tilde{x} = x + \varepsilon$, where x is the true level of consumption while ε is the bias between the estimate and true consumption. Then consumer's problem becomes

$$\max_{x,y} u(x, y) \qquad s.t. \quad p\tilde{x} + y = I \quad and \;\; x \leq E$$

In this case the budget constraint is equivalent to $px + y = I - p\varepsilon$ and thus the information uncertainty essentially translates into an income effect. If $\varepsilon < 0$ meaning that the agent under-estimates his electricity consumption, it is equivalent to having an increase in the budget constraint. Thus consumers will consume more electricity than the pre-paid case. The red lines in Figure 4a show the budget constraint and the utility maximization problem for such post-pay customers. The new budget constraint shift outwards and it is tangent to the utility curve at a higher value of x.

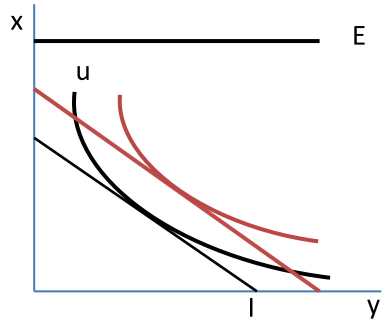

Figure 4a. Utility maximization problem for post-pay customers (under-estimate their electricity consumption)

If $\varepsilon > 0$ meaning that the agent over-estimates his electricity consumption, it is equivalent to having a decrease in the budget constraint. Thus consumers will consume less electricity than the pre-paid case. The tangent point of the red lines in Figure 4b shows the solution to the utility maximization problem for such post-pay customers. The new budget constraint shift inwards and it is tangent to the utility curve at a lower value of *x*.

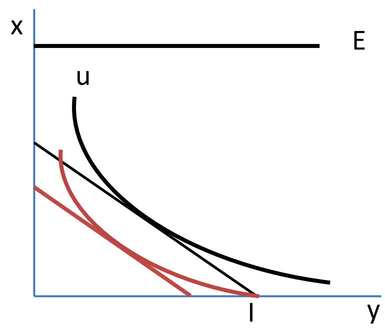

Figure 4b. Utility maximization problem for post-pay customers (over-estimate their electricity consumption)

Thus through the information provision mechanisms, pre-paid programs can either increase or decrease electricity consumption compared to a post-pay scheme.

3.4 Costs of being disconnected

In a pre-paid program, once the credit is used up, electricity would be disconnected and the agent would incur disutility from the disconnection. In addition, in most existing pre-paid systems, customers need to go to designated locations to charge their pre-paid card and thus incur further cost (time and travel). To capture these effects from disconnection, we add a cost component *C* into the budget constraint.

$$\max_{x,y} u(x, y) \qquad s.t. \quad px + y + C = I \quad and \;\; x \leq E$$

This is equivalent to have a decreased budget constraint and thus consumption of electricity will be reduced. The tangent point of the green lines in Figure 5 shows the solution to the utility maximization problem for such pre-paid customers while incorporating this extra cost. Figure 5 shows that in this case, the budget constraint shifts inwards and is tangent to the utility curve at a lower value of x.

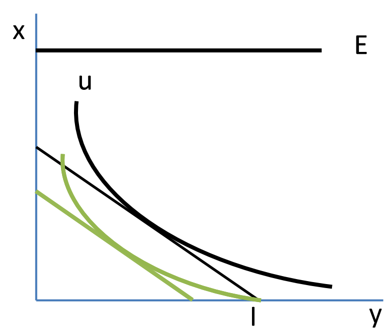

Figure 5. Utility maximization problem for pre-paid customers (with extra cost of pre-paid program)

4. Empirical strategy and study design

4.1 Empirical strategy

The standard residential price plan is called E-23 plan for SRP customers. In this study, we estimate the casual impact on electricity consumption of switching to M-power (the prepaid plan) from the standard residential price plan. However, M-Power is a voluntary plan and there will be selection-bias issues. Un-observable factors such as household budgeting skills, ability to reduce energy consumption, and willingness to be more conscious about energy consumption can affect both the participation of pre-paid program and electricity consumption. For example, participants of the pre-paid program could be those that have poorer household budgeting skills in the first place and even if they switched to the pre-paid program, they still can't manage their energy expenditure better, which will lead to an under-estimate of the treatment effects. It is also possible that households that are willing to switch to the pre-paid program might be those that have better ability to reduce their energy consumption because they have fewer people in the household, which will lead to an over-estimate of the treatment effects. It is also possible that consumers who are more conscious about their energy consumption want to switch to the pre-paid program, which again will lead to an over-estimate of the treatment effects.

In order to eliminate the selection bias and to estimate the causal impact, we apply a combination of matching and difference-in-differences (DID) approaches. Fowlie et al. (2012) use a similar matching and DID approach to analyze emission trading programs. Matching methods select a control group that is as similar to the treatment group as possible prior to the treatment (Fowlie et al., 2012), which is referred to as a Nonequivalent Control Group Design (Campbell & Stanley, 1963). The Electric Power Research Institute (EPRI) Research Protocol (EPRI, 2010a) states that "the objective of this approach is to create a non-equivalent control group that is as similar as possible to the treatment group formed by volunteer participants."

In the case of voluntary program participation, researchers can implement a matching method if the following three assumptions hold: 1) each observation has independent and identical distribution (i.i.d. sample); 2) if conditional on the observed control variables, the participation and the outcome variables are independent or that only observable factors influence participation and the outcome variables simultaneously, the so-called selection on observables (Conditional Independence or CIA); 3) given a level of the observed control variables, the probability of a subject participating in the program is between zero and one (Common Support or CS). In a case where selection is based on unobservable attributes, (meaning that assumption 2 is violated), researchers can implement a combination of matching and difference-in-differences (DID) estimator such as panel regressions (which includes flexible fixed effects to eliminate the unobservable factors).

In this study, Assumptions 1 and 3 can be justified to hold: conditional on the observables, each residential customer is likely to be independent of each other and has a similar distribution of energy consumption (Assumption 1); given a level of the key observable attributes – location, arrearage amount and energy consumption stratum – there are both customers that volunteered to participate in the pre-paid program and customers that did not (Assumption 3). Assumption 2 is harder to justify and also generally not testable, so we apply a DID approach.

Exact matching is not always feasible. Inexact matching requires a measure of "distance" between any two observations, *i* and *j*. This proposal adopts Euclidian-type distance matching (Rosenbaum and Rubin 1983). Euclidian-type distance matching is to find a control household that has the shortest distance with the treatment household where the distance is $d_{ij}=(x_i-x_j)'\ W\ (x_i-x_j)$ and $\boldsymbol{x}$ is a vector of observed attributes prior to the start of treatment and W is a weight matrix. Different matching algorithms including single nearest neighbor, k-nearest neighbor and kernel matching were tried to find the optimal control group.

We also checked the balancing statistics of the matching results. In order to have valid estimates on the treatment effects using the matching approach, it is important to ensure that the treatment group and control group are indeed comparable on pre-treatment attributes. This is called balancing of groups. Two important balancing statistics are used to test the sample equivalence: standardized mean difference (SMD) to check for sample means and variance ratios (VRs) to check for distribution and higher-order sample moments (Linden and Samuels, 2013). SMD for a given attribute X_j is defined as

$$smd_j = \frac{|\bar{X}_{jT} - \bar{X}_{jC}|}{\sqrt{\frac{(S_{jT})^2 + (S_{jC})^2}{2}}} \quad ,$$

where the numerator is the absolute difference in average X_j between the treatment and control groups (subscripts T and C, respectively); the denominator is the average standard deviation of the two groups. Although there is no empirical evidence in the literature on using which cut-off point to define balance, Normand et al. (2001) suggest that if SMD is greater than 0.1 and Rubin(2001) suggest that if SMD is greater than 0.25, then it implies that treatment and control groups are not balanced in means.

VR for a given attribute X_j is defined as

$$VR_j = \frac{(S_{jT})^2}{(S_{jC})^2} \quad ,$$

where S_{jT} is the standard deviation of X_j in the treatment group and S_{jC} is the standard deviation of X_j in the control group. Rubin suggests that if VR is greater than 2 or less than 0.5, it implies imbalance of the distribution of the two groups.

4.2 Study design

The general study design is summarized in Table 1. Summer and winter studies are separate. For the summer study, the treatment group customers are those who switched to the pre-paid program between November 2008 and April 2009. The pre-test period is May 2008 to Oct 2008 and the post-test period is May 2009 to Oct 2009. For the winter study, the treatment group customers are those who switched to the pre-paid program between May 2009 and Oct 2009. The pre-test period is Nov 2008 to April 2009 and the post-test period is Nov 2009 to April 2010.

<Insert Table 1 here>

Customers' meter reading dates can change after they switch to the pre-paid program, which could potentially affect the evaluation. For example, before the switch, the meter reading date of a customer could be on the 1st of each month while after the switch, the reading date could be 15th. Energy consumption pattern can change within 15 days because of variation in weathers within 15 days. Thus we filtered the pre-paid customers to only include those whose post-test meter reading dates are within +/- 7 days of the pre-test dates.

The pre-test period customer level attributes are used for matching. For a pre-paid customer, a control customer who is located in the same city, zip code and street and that has the most similar pre-test energy consumption level as the treatment customer is identified.

5. Data

There are 363 pairs of control and treatment customers for the summer study and 1,278 pairs for the winter study. Table 2 shows the summary statistics of the energy usage for the pre-paid customers and their control customers as well as the balance check results for sample equivalence. For the summer study, before the treatment customers switched to the pre-paid program, the treatment and control customers had similar daily energy usage levels of about 57~58 kWh. After the switch, the energy usage level of control customers stayed the same at about 58 kWh while the treatment customers dropped their energy usage to 52 kWh. Similarly, for the winter study, the treatment and control customers had similar energy usage levels before the switch while after the switch the treatment customers dropped their energy usage while control customers' stayed the same.

<Insert Table 2 here>

The balancing statistics SDM is 0.05 for the summer study and 0.01 for the winter study, with both below 0.1, which suggests that the control and treatment groups are equivalent in terms of sample means. The statistics VR is 1.26 for the summer study and 1.25 for the winter study, with both below 2 and greater than 0.25, which suggests that the sample distribution between control and treatment groups are also equivalent.

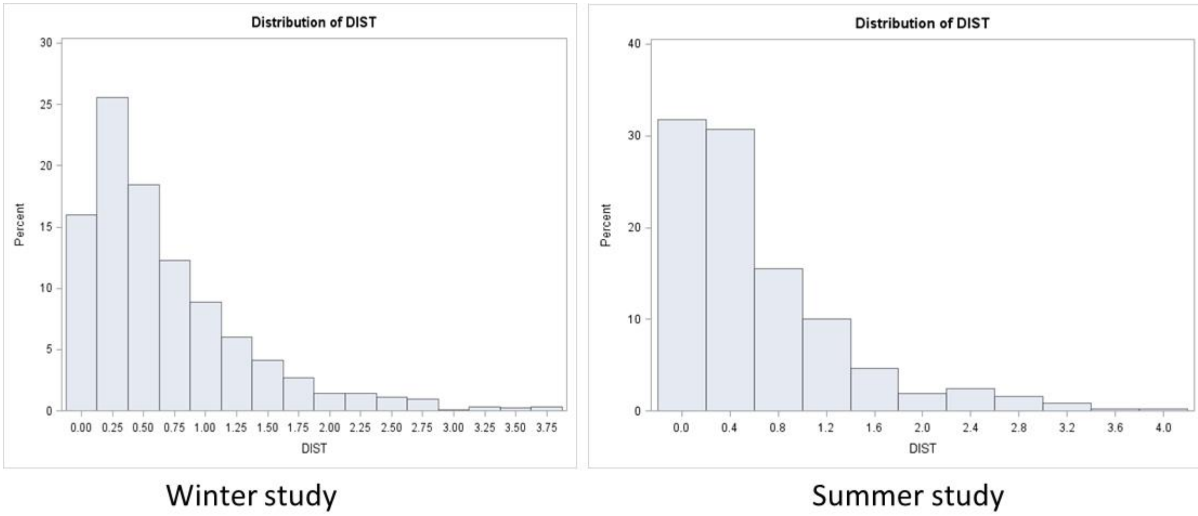

Figure 6. Distribution of the distance (in miles) between a pair of control and treatment customer

Figure 6 shows the distribution of the distance (in miles) between a pair of control and treatment customer. Most control customers are located within 1 miles of distance to their treatment customers and this can ensure the elimination of complicating factors from being in different neighborhoods.

6. Results

We first conduct statistical two sample test to evaluate whether there are statistically significant differences between the control and treatment groups in their post- and pre- test electricity consumption. Table 3 lists the results. The left hand side column of Table 3 uses the traditional subtraction DID method, which means testing T_{post}-T_{pre}=C_{post}-C_{pre}. T_{post} is the outcome variable (e.g. energy consumption) of the treatment group after the treatment and T_{pre} is the outcome variable of the treatment group prior to the treatment. Similarly, C_{post} is the outcome variable (e.g. energy consumption) of the control group after the treatment and C_{pre} is the outcome variable of the control group prior to the treatment. Traditional subtraction DID estimator of the treatment effect is $\hat{\beta}^{DID} = (\mathrm{T}_{\mathrm{post}} - \mathrm{T}_{\mathrm{pre}}) - (\mathrm{C}_{\mathrm{post}} - \mathrm{C}_{\mathrm{pre}})$. The right hand side column uses the percentage DID method, which means testing $\mathrm{T}_{\mathrm{post}}/\mathrm{T}_{\mathrm{pre}}=\mathrm{C}_{\mathrm{post}}/\mathrm{C}_{\mathrm{pre}}$. We also conduct the percentage method because this ensures that every customer in the small samples has equal impact in the energy analyses.

<Insert Table 3 here>

We conduct both t-test and the non-parametric test (Wilcoxon sighed-ranks test). The p-value shows that both tests are statistically significant at 1% level, which suggests that the control and treatment customers had statistically significant differences in their energy usage after the treatment customers switched to the pre-paid program. From the traditional subtraction DID method, in the summer, pre-paid customers reduced their average daily energy consumption by -6.64-0.24=6.88 kWh; in the winter, pre-paid customers reduced their average daily energy consumption by -4.64-0.31=4.95 kWh. From the percentage method, pre-paid customers saved their energy consumption by 0.9-1=10% in the summer and by 0.86-1=14% in the winter.

We then conduct panel regression methods to control for more characteristics. The complete panel regression model is as follows:

$$kWh_{it}=\alpha+ \beta * M\text{-}Power_{it}+\lambda * Arrear_{i} +\delta * Arrear_{i} * M\text{-}Power_{it} + \sum_{1}^{K} \theta_k * Usage\_stratum_{ki} + \sum_{1}^{K} \eta_k * Usage\_stratum_{ki} * M\text{-}Power_{it} + \alpha_i +\varepsilon_t+\tau_{it} \quad (1),$$

where *i* indicates individual customer; *t* indicates time period; *kWh* is the average daily energy consumption; *M-Power* is a dummy variable that is equal to one if customer *i* is on M-Power program (pre-paid program) at time *t*; *Arrear* is the amount of money a customer owed to the utility company prior to the start of the treatment period, which can serve as a proxy for customer wealth level with higher amount of arrear indicating lower level of wealth*; Usage_stratum* is a series of dummy variables indicating the pre-test energy consumption categories (S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850; S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800; S5: 1800≤summer monthly kWh<2600; S6: summer monthly kWh ≥ 2600); α_i is individual fixed effects and ε_t is time fixed effects.

We estimate different model specifications of equation (1). Tables 4 & 5 are the panel regression results for summer study. Table 4 uses random effects model [6] and Table 5 uses fixed effects model. The coefficient for the M-Power dummy variable measures the impact of the M-Power program on daily energy usage, and it is negative and statistically significant for all models, indicating that M-Power program leads to statistically significant energy reductions. Models 1-8 have different control covariates. Models 1-3 show that on average, M-Power program in the summer reduces average daily energy usage by 6.8~7.3 kWh. At the mean pre-treatment energy usage level of 58.656 for the treatment customers, this energy reduction amounts to about 12% energy savings. In Models 4 &5, the coefficient of the interaction term *Arrear*M-Power* is negative and statistically significant, which indicates that customers with higher arrear amount or lower wealth level tend to save more energy. The coefficient of -0.00630 in Model 4 implies if a customer's arrear of the month prior to switching to M-Power is $100 higher, the customer will reduce his/her energy consumption by about 0.6 kWh more. This further decrease in energy consumption by customers with higher arrear could result from the fact that higher-arrear customers have lower income or tighter budget for energy consumption. Model 5 adds the interaction terms between energy usage stratum dummies and M-Power. The base case is highest usage stratum. The coefficient for *M-Power* in Model 5 is the energy

[6] We conduct random effects models in addition to fixed effects models because there are several time-invariant variables whose coefficients are of interest to the econometrician and policy makers.

reduction by the customers in the highest usage stratum in the base case, a daily reduction of 12.8 kWh. The coefficients for the interaction terms between energy usage stratum dummies and M-Power are positive and statistically significant, indicating that compared to higher usage customers, lower usage customers save less on their energy consumption in terms of kWh.

<Insert Tables 4&5 here>

Similar results are found in Table 5 which lists the fixed effects model results for the summer study. From Model 6, M-Power program in the summer reduces average daily energy usage by 6.89 kWh or 6.8/58.656=12%. Model 7 shows that if a customer's arrear of the month prior to switching to M-Power is $100 higher, the customer will reduce his/her energy consumption by about 0.7 kWh more. Model 8 also shows that higher usage customers save more kWh on their energy consumption.

Tables 6 & 7 list the results for winter study. Models in Table 6 use random effects and models in Table 7 use fixed effects. Models 9, 10, 11 in Table 6 and Model 14 in Table 7 show that on average, M-Power reduces customers' winter daily average energy consumption by 4.9~5.1 kWh. At the mean pre-treatment energy usage level of 32.260 for the treatment customers, this energy reduction amounts to about 15% energy savings. Models 12 & 15 show that higher-arrear or lower-wealth customers reduce their winter daily energy consumption more, consistent with the summer results. From Model 12, the coefficient for Arrear*M-Power is 0.00752, indicating that if a customer's arrear of the month prior to switching to M-Power is $100 higher, the customer will reduce his/her energy consumption by about 0.75 kWh more. Model 16 shows that higher usage customers save more kWh on their energy consumption in the winter, but different from the summer results, winter results show that such change in energy reduction is not monotonic. Stratum 3 customers saved the least compared to other stratum customers.

<Insert Tables 6&7 here>

Tables 8 & 9 combine the summer and winter study in the estimation. The interaction term *Winter*M-Power* can test whether consumers save more energy in the winter than they do in the summer. The coefficients for *Winter*M-Power* are all statistically significant and positive, indicating that consumers save more electricity in the summer.

<Insert Tables 8&9 here>

7. Robustness checks

Although the combination of matching and DID methods can eliminate the selection bias originated from time-invariant and entity-invariant unobservables, it is likely that there are time-variant individual or neighborhood factors that can alter consumers' participation in pre-paid program and also their electricity consumption, causing biased estimation of the treatment effects. To deal with these time-variant factors, we conduct the following robustness checks.

Wealth stratum-time fixed effects: It is likely that households within the same wealth level groups face similar shocks such as employment status shock and income shock. We use arrear amount as the proxy for wealth level and create five wealth level stratum (Stratum 1: arrear<0 meaning that utilities actually owe the consumers money; Stratum 2: 0≤ arrear<200; Stratum 3: 200≤ arrear<500; Stratum 4: 500≤ arrear<1000; Stratum 5: arrear ≥ 1000). Then we include the wealth stratum-time fixed effects (ε_{wt}) in the panel regression model as shown in equation (2). For robustness checks we are mainly interested in the average treatment effects of all categories of customers and thus we do not include variables involving *Arrear* or *Usage_stratum* as explanatory variables.

$$kWh_{it}=\alpha+ \beta*M\text{-}Power_{it} + \alpha_i +\varepsilon_{wt}+\tau_{it} \qquad (2)$$

Zip code-time fixed effects: Neighborhood time-variant factors such as peer effects and neighborhood infrastructure development might also influence the participation in pre-paid plan and energy consumption. Thus we include a zip code-time fixed effects (ε_{zt}) as shown in equation (3) to control for these neighborhood time-variant factors.

$$kWh_{it}=\alpha+ \beta*M\text{-}Power_{it} + \alpha_i +\varepsilon_{zt}+\tau_{it} \qquad (3)$$

Entity-year fixed effects: Ideally entity-time fixed effects at a coarser time level can be used to control for individual level time-variant unobservables at the coarser time level. Our dataset has the monthly electricity bill information, which means entity-year or entity-quarter fixed effects can be utilized. For summer study, the pre-test and post-test periods are in two separate years. Thus the treatment variable $M\text{-}Power_{it}$ does not vary for an individual within a given time frame finer than a year for summer study. As a result, we can't include entity-year fixed effects in the summer study. However, winter study spans three years and for the treatment groups the treatment variable $M\text{-}Power_{it}$ does vary in 2009. Thus we include the entity-year fixed effects (α_{iy}) for the winder study as the third robustness check and make individual observation at monthly level, as shown in equation (4).

$$kWh_{it}=\alpha+ \beta*M\text{-}Power_{it} + \alpha_{iy} +\varepsilon_{t}+\tau_{it} \qquad (4)$$

Results of the robustness checks are listed in Table 10 and the results show that the pre-paid plan still has statistically significant influence on electricity consumption reduction.

<Insert Table 10 here>

8. Welfare and policy implications

Surveys show that on average M-Power customers charge their pre-paid cards 3~4 times per month and customers drive 2-3 miles (round trip) to purchase the power (EPRI, 2010b). Assuming a 23.3 mpg fuel economy in 2010 (BTS, 2014) and 3$/gallon gas price, this amounts to extra monetary cost of $0.3 per month. Because the pay centers are usually located at grocery stores so customers can charge their cards while doing grocery shopping. Thus the marginal cost of time to charge the cards is low. On average, M-Power customers save 6kWh per day. SRP residential average electricity price is $0.1/kWh. So the saved energy cost is $0.6 per day or $18 per month, which is significantly higher than the monthly monetary cost of going to the pay center. Thus there is apparent monetary gain of pre-paid customers. Future analyses will be conducted to evaluate comprehensive welfare impact, when data on the cost and benefit of utility companies is available.

In addition to monetary rewards to the consumers, pre-paid electricity plan also reduces the negative externalities associated with consuming fossil fuel-generated electricity such as carbon emissions and emissions of other environmental pollutants. With the challenge of energy independence and climate change, policy makers need to identify cost-effective and efficient policy instruments and programs to reduce consumption of fossil fuels. This study shows that pre-paid electricity plan can be an effective instrument to reduce carbon emissions and energy consumption and in the meanwhile have the potential to achieve welfare gain. Compared to other types of energy behavioral programs, pre-paid plan achieves higher percentage of energy savings – 12% as found in this study. For example, Allcott (2011b) finds that behavioral interventions of providing home energy reports compared to peers can save energy consumption by about 2%. Faruqui et al. (2010) finds that in-home displays (IHDs) alone reduce energy consumption by about 7%. The reasons for the much higher energy reduction rate of pre-paid program could be, as demonstrated in the theoretical framework, that pre-paid plan can significantly reduce the inattention problem on energy consumption. In addition, the pre-paid program analyzed in this study also installs IHDs and there is still additional 5% savings compared to programs of only IHDs. This means that the payment procedure itself of the pre-paid program also contributes to energy savings. Thus it is important to bring policy makers' attention to pre-paid electricity programs as potential instruments for reducing carbon emissions and energy consumption.

9. Conclusions

In a pre-paid electricity plan, customers pay in advance for the amount of electricity they can consume. When the pre-paid amount is close to being used up, customers then add money to their accounts in order to continue electricity usage. A pre-paid plan can help energy conservation and thus can be a potential compliance mechanism for the recent EPA's proposed rule on reducing carbon emissions from existing power plants (EPA, 2014).

This paper first demonstrates using basic economic theory that here are four possible channels for the reduction in electricity consumption from a pre-paid plan: nudging, price effects, information provision, and costs of being disconnected. Then, using customer level residential billing data from 2008-2010 of a major utility company in Phoenix metropolitan area, this study adopts a matching approach and a difference-in-differences method to estimate empirically the impact of switching to a pre-paid electricity plan on residential electricity consumption, after correcting for selection bias. Findings indicate that switching to a pre-paid program is associated with a 12% reduction in electricity consumption. We also explore the heterogeneity in the response to pre-paid electricity pricing by wealth level. Using arrear amount as a proxy for wealth, we find that customers with lower level of wealth tend to experience greater electricity reduction after the switch. In addition, results show that pre-paid customers save more electricity in the summer than winter, which has important implication for managing peak demand and load shape for utility companies since summer is when system peak demand usually happens.

The exact mechanisms for the energy conservation need to be empirically tested. SRP plans to implement online SmartCard charging platform, which can significantly reduce the cost of going to a pay center. If after implementing the online platform there is still conservation in energy, the conservation would then come from nudging, price effects and information provision channels. Further experiments such as comparing pre-paid programs with and without in-home displays can help disentangle the impacts between nudging and information provision.

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Tables

Table 1. Summary of study design

	Summer study	Winter study
Pre-test period (matching period)	05/2008-10/2008	11/2008-04/2009
Treatment starting period	11/2008 – 04/2009	05/2009 and 10/2009
Post-test period	05/2009-10/2009	11/2009-04/2010

Matching criteria

1. Location: same city, zip code, and street name
2. Pre-test consumption level: average monthly kWh

Table 2. Summary statistics for summer and winter studies

Summer study: pre-test period (May-Oct, 2008); post-test period (May-Oct, 2009)

Variable		Obs	Mean	Std. Dev.	Min	Max
M-Power customers (daily kWh)	pre-test period	363	58.656	25.366	13.315	188.736
	Post-test period	363	52.013	22.639	8.239	138.315
Control customers (daily kWh)	pre-test period	363	57.373	22.364	12.750	120.276
	Post-test period	363	57.618	21.701	13.141	124.354

Balance check for the treatment and control groups: SDM=0.05 VR=1.26

Winter study: pre-test period (Nov. 2008-April, 2009); post-test period (Nov. 2009-April, 2010)

Variable		Obs	Mean	Std. Dev.	Min	Max
M-Power customers (daily kWh)	pre-test period	1278	32.260	14.723	6.154	95.495
	Post-test period	1278	27.617	13.148	4.798	94.590
Control customers (daily kWh)	pre-test period	1278	32.071	12.409	7.500	102.842
	Post-test period	1278	32.382	12.154	7.903	88.238

Balance check for the treatment and control groups: SDM=0.01 VR=1.25

Table 3: T-tests and non-parametric tests

Summer study					
Subtraction method: test for T_{post}-T_{pre}=C_{post}-C_{pre}			Percentage method: test for $(T_{post}/T_{pre})/(C_{post}/C_{pre})=1$		
Average T_{post}-T_{pre}= -6.64 Average C_{post}-C_{pre}= 0.24			Average $(T_{post}/T_{pre})/(C_{post}/C_{pre})$=0.90		
	Test statistics	P-value		Test statistics	P-value
T-test	t=-10.2706	0.0000	T-test	t= -8.4511	0.0000
Wilcoxon signed-rank test	z=-10.037	0.0000	Wilcoxon signed-rank test	z=-9.715	0.0000

Winter study					
Subtraction method: test for T_{post}-T_{pre}=C_{post}-C_{pre}			Percentage method: test for $(T_{post}/T_{pre})/(C_{post}/C_{pre})=1$		
Average T_{post}-T_{pre}= -4.64 Average C_{post}-C_{pre}= 0.31			Average $(T_{post}/T_{pre})/(C_{post}/C_{pre})$=0.86		
	Test statistics	P-value		Test statistics	P-value
T-test	t=-21.7461	0.0000	T-test	t= -22.7998	0.0000
Wilcoxon signed-rank test	z=-20.781	0.0000	Wilcoxon signed-rank test	z=-20.283	0.0000

Table 4. Random effects model of summer study. Dependent variable: average daily kWh

Model number		(1)	(2)	(3)	(4)	(5)
M-Power: dummy variable indicating whether on M-Power program		-6.780*** (0.687)	-7.310*** (0.695)	-6.897*** (0.647)	-5.284*** (0.912)	-12.78*** (1.256)
Arrear			0.0185*** (0.003)	0.00401*** (0.001)	0.0202*** (0.003)	0.00528*** (0.001)
Arrear*M-Power					-0.00630*** (0.002)	-0.00200 (0.002)
Stratum dummy variables [1] Base case: S5, the highest usage stratum	S1			-69.41*** (1.511)		-72.37*** (1.599)
	S2			-56.28*** (1.119)		-59.14*** (1.184)
	S3			-44.44*** (0.968)		-46.41*** (1.025)
	S4			-29.20*** (0.863)		-30.82*** (0.915)
Interaction terms between stratum variables and M-Power Base case: S5, the highest usage stratum	S1*M-Power					12.01*** (2.12)
	S2*M-Power					11.59*** (1.58)
	S3*M-Power					7.979*** (1.35)
	S4*M-Power					6.468*** (1.19)
Constant		58.01*** (0.856)	54.94*** (0.992)	89.38*** (0.761)	54.66*** (0.996)	90.74*** (0.791)
Time random effects		Y	Y	Y	Y	Y
Entity random effects		Y	Y	Y	Y	Y
# of observations		1452	1452	1452	1452	1452

Note: Clustered standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
[1] S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850;
S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800;
S5: 1800≤summer monthly kWh<2600.

Table 5. Fixed effects model of summer study. Dependent variable: average daily kWh

Model number		(6)	(7)	(8)
M-Power: dummy variable indicating whether on M-Power program		-6.888*** (0.702)	-4.420*** (0.927)	-13.38*** (1.38)
Arrear*M-Power			-0.00752*** (0.002)	-0.00237 (0.002)
Interaction terms between stratum variables and M-Power [1] Base case: S5, the highest usage stratum	S1*M-Power			13.04*** (2.26)
	S2*M-Power			12.68*** (1.68)
	S3*M-Power			9.134*** (1.43)
	S4*M-Power			7.679*** (1.27)
Constant		58.01*** (0.25)	58.01*** (0.25)	58.01*** (0.23)
Time fixed effects		Y	Y	Y
Entity fixed effects		Y	Y	Y
# of observations		1452	1452	1452

Note: Clustered standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
[1] S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850; S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800; S5: 1800≤summer monthly kWh<2600.

Table 6. Random effects model of winter study. Dependent variable: average daily kWh

Model number		(9)	(10)	(11)	(12)	(13)
M-Power: dummy variable indicating whether on M-Power program		-4.936***	-5.105***	-4.927***	-4.018***	-8.278***
		(0.227)	(0.230)	(0.227)	(0.304)	(0.454)
Arrear			0.00645***	0.000192	0.00751***	0.00111
			(0.001)	(0.001)	(0.001)	(0.001)
Arrear*M-Power					-0.00478***	-0.00199**
					(0.001)	(0.001)
Stratum dummy variables [1] Base case: S6, the highest usage stratum	S1			-35.79***		-37.21***
				(3.20)		(3.26)
	S2			-29.14***		-30.54***
				(0.94)		(0.96)
	S3			-25.65***		-27.16***
				(0.63)		(0.64)
	S4			-20.95***		-22.29***
				(0.54)		(0.56)
	S5			-13.71***		-14.81***
				(0.46)		(0.47)
Interaction terms between stratum variables and M-Power Base case: S6, the highest usage stratum	S1*M-Power					5.736**
						(2.803)
	S2*M-Power					5.514***
						(0.840)
	S3*M-Power					5.987***
						(0.567)
	S4*M-Power					5.321***
						(0.490)
	S5*M-Power					4.348***
						(0.412)
Constant		32.17***	31.49***	46.23***	31.37***	47.09***
		(0.26)	(0.29)	(0.39)	(0.29)	(0.40)
Time random effects		Y	Y	Y	Y	Y
Entity random effects		Y	Y	Y	Y	Y
# of observations		5112	5112	5112	5112	5112

Note: Clustered standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01
[1] S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850;
S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800;
S5: 1800≤summer monthly kWh<2600; S6: summer monthly kWh ≥ 2600.

Table 7. Fixed effects model of winter study. Dependent variable: average daily kWh

Model number		(14)	(15)	(16)
M-Power: dummy variable indicating whether on M-Power program		-4.955*** (0.234)	-3.514*** (0.309)	-8.021*** (0.471)
Arrear*M-Power			-0.00617*** (0.0009)	-0.00259*** (0.0009)
Interaction terms between stratum variables and M-Power [1] Base case: S6, the highest usage stratum	S1*M-Power			5.814** (2.871)
	S2*M-Power			5.153*** (0.862)
	S3*M-Power			5.893*** (0.581)
	S4*M-Power			5.110*** (0.502)
	S5*M-Power			4.272*** (0.422)
Constant		32.17*** (0.083)	32.17*** (0.082)	32.17*** (0.081)
Time fixed effects		Y	Y	Y
Entity fixed effects		Y	Y	Y
# of observations		5112	5112	5112

Note: Clustered standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01
[1] S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850;
S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800;
S5: 1800≤summer monthly kWh<2600; S6: summer monthly kWh ≥ 2600.

Table 8. Random effects model of all year study. Dependent variable: average daily kWh

Model number		(17)	(18)	(19)	(20)	(21)
M-Power: dummy variable indicating whether on M-Power program		-6.858*** (0.391)	-7.149*** (0.394)	-6.910*** (0.388)	-5.446*** (0.471)	-12.26*** (0.702)
Arrear			0.0103*** (0.001)	0.00246*** (0.0009)	0.0115*** (0.0012)	0.00350*** (0.0009)
Arrear*M-Power					-0.00530*** (0.0008)	-0.00235*** (0.0008)
Winter		-25.82*** (0.66)	-25.21*** (0.66)	-37.02*** (0.50)	-25.13*** (0.65)	-37.55*** (0.50)
Winter*M-Power		1.946*** (0.403)	1.979*** (0.403)	1.903*** (0.397)	1.482*** (0.409)	4.000*** (0.44)
Stratum dummy variables [1] Base case: S6, the highest usage stratum	S1			-58.51*** (1.60)		-61.23*** (1.64)
	S2			-38.83*** (0.88)		-40.93*** (0.90)
	S3			-29.65*** (0.67)		-31.33*** (0.68)
	S4			-21.39*** (0.59)		-22.83*** (0.61)
	S5			-10.83*** (0.53)		-11.76*** (0.54)
Interaction terms between stratum variables and M-Power Base case: S6, the highest usage stratum	S1*M-Power					10.76*** (1.41)
	S2*M-Power					8.283*** (0.791)
	S3*M-Power					6.596*** (0.597)
	S4*M-Power					5.667*** (0.530)
	S5*M-Power					3.634*** (0.467)
Constant		57.99*** (0.58)	56.30*** (0.61)	82.93*** (0.68)	56.09*** (0.61)	84.30*** (0.69)
Time random effects		Y	Y	Y	Y	Y
Entity random effects		Y	Y	Y	Y	Y
# of observations		6564	6564	6564	6564	6564

Note: Clustered standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
[1] S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850;
S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800;
S5: 1800≤summer monthly kWh<2600; S6: summer monthly kWh ≥ 2600.

Table 9. Fixed effects model of all year study. Dependent variable: average daily kWh

Model number		(22)	(23)	(24)
M-Power: dummy variable indicating whether on M-Power program		-6.940***	-4.755***	-11.81***
		(0.397)	(0.475)	(0.73)
Arrear*M-Power			-0.00666***	-0.00308***
			(0.0008)	(0.0008)
Winter*M-Power		2.000***	1.369***	3.960***
		(0.407)	(0.411)	(0.449)
Interaction terms between stratum variables and M-Power [1]	S1*M-Power			10.58***
				(1.45)
	S2*M-Power			7.971***
				(0.811)
Base case: S6, the highest usage stratum	S3*M-Power			6.456***
				(0.612)
	S4*M-Power			5.476***
				(0.542)
	S5*M-Power			3.467***
				(0.478)
Constant		37.88***	37.88***	37.88***
		(0.084)	(0.084)	(0.081)
Time fixed effects		Y	Y	Y
Entity fixed effects		Y	Y	Y
# of observations		6564	6564	6564

Note: Clustered standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
[1] S1: summer monthly kWh<400; S2: 400≤summer monthly kWh<850;
S3: 850≤summer monthly kWh<1300; S4: 1300≤summer monthly kWh<1800;
S5: 1800≤summer monthly kWh<2600; S6: summer monthly kWh ≥ 2600.

Table 10. Results of robustness checks. Dependent variable: average daily kWh

Robustness check type	Wealth stratum-time fixed effects		Zip code-time fixed effects		Entity-year fixed effects
Study phase	Summer	Winter	Summer	Winter	Winter only
M-Power: dummy variable indicating whether on M-Power program	-5.776***	-4.188***	-6.097***	-4.243***	-4.954***
	(0.961)	(0.316)	(1.053)	(0.315)	(0.234)
Constant	57.703***	32.312***	57.884***	32.324***	32.425***
	(0.456)	(0.089)	(0.501)	(0.089)	(0.079)
Entity fixed effects	Y	Y	Y	Y	
Wealth stratum-time fixed effects	Y	Y			
Zip code-time fixed effects			Y	Y	
Month fixed effects					Y
Entity-year fixed effects					Y
# of observations	1452	5112	1452	5112	30672

Note: Clustered standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01