Demand Impact of a Critical Peak Pricing Program: Opt-in and Opt-out Options, Green Attitudes and Other Customer Characteristics

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ABSTRACT

In this paper, we provide demand impact estimates of a critical peak pricing (CPP) program tested in the summer of 2011. We develop econometric models that examine demand responses of participants in "opt-in," "opt-out," and "tech only" CPP programs. Opt-out customers received bill protection while tech only customers received in-home displays alerting them of critical peak times, but they were not placed on the CPP rate. Our results indicate that opt-in customers reduced critical peak period demand the most while opt-out customers' appear to attenuate their reduction because of bill protection. Additionally, we refine our findings using participant survey responses. In general, we find participants in test groups whose environmental or "green" attitude is high had the strongest demand response.

Keywords: Critical peak pricing, Dynamic rates, Demand response, Average load impact, Opt-in, Opt-out, Pilot design, Stratified random sampling

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1. INTRODUCTION

Sioux Valley Energy (SVE) is an electric distribution cooperative serving approximately 21,000 electric customers in Minnesota and South Dakota. In 2009, SVE won a Smart Grid Investment Grant to complete the installation of a system-wide advanced metering infrastructure (AMI), including necessary backhaul equipment, communication systems, and smart meters. With the help of this infrastructure, SVE began to explore the impact of providing customers with time-of-use electricity rates. Following an initial investigation of various programs, SVE decided to run an experiment by offering rates that loosely correlated with the wholesale electricity prices it faced on specific days and hours.

Accordingly, from June 1, 2011 through August 31, 2011, SVE ran a CPP pilot. The goal of the pilot was to explore a dynamic pricing program as a means of engaging customers and promoting curtailment of electricity use during peak times. In addition, SVE wanted to determine whether it would be prudent to offer a CPP rate to all its customers and, if so, how best to accomplish this.

There are a few practical ways a utility can fully deploy a program of this type. First, it can seek volunteers who sign up for its critical peak pricing program. Second, it can make the

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critical peak pricing program the default, thereby placing all of its customers on the CPP rate. Third, it can equip all its customers with in-home displays that alert them of critical peak periods. On this third option, the customers' rate stays the same; the benefit comes from curtailment with no monetary reward for the customer. In addition, the second of these choices cannot be practically applied without offering the choice to opt out of the program and/or bill protection, since it would risk severe customer backlash and termination of the program. Attracting customers to participate in a CPP program on an opt-in basis, however, has its own shortcomings. As Matsukawa (2001) notes, the demand effect of an opt-in time-varying rate can be distorted as customers whose load profiles are less peaky self-select into this rate.[1]

In addition, time-varying prices, such as CPP, are "carrot–and–stick" options that reward as well as punish users for peak time use. Since off-peak rates are often significantly low, customers that reduce their critical peak period use enjoy the "carrot" end of the program in the form of lower total bills. Those that fail to do so can experience increases in their total payment since the significantly higher cost of power during critical peak times is not offset by the lower cost during off-peak periods.[2] This is the "stick" end of the program, which may pose political and regulatory challenges that a utility needs to consider.

For instance, many customer stakeholders favor programs that offer customers "carrot" only options. Alexander (2010) is one such example. She advocates the use of demand response programs, such as peak time rebates (PTR), to reduce peak time usage over dynamic pricing programs such as CPP. Alexander argues that dynamic pricing exposes residential consumers to volatile electricity prices; shifts the risk or responsibility of handling wholesale price volatility from utilities that are better equipped for this to consumers who are not; and subjects those on fixed incomes, such as seniors and the poor, to food insecurity and health hazards by discouraging air conditioning or electric heat use during hot summer or cold winter days. She argues that the "carrot" only option leads to peak time demand reduction without exposing consumers to undue hardships.[3]

Therefore, exploring not only the demand effect of dynamic prices with opt-in participation, but also with opt-out participation coupled with bill protection, which converts this program from a "carrot-and-stick" mechanism into a "carrot" only one, was important in SVE's experimental undertaking. It informs the extent of demand reductions that are possible once a program is fully deployed.

SVE thus set up its dynamic pricing experiment based on test groups composed of opt-in and opt-out participants placed on a CPP rate, and a third group that faced the standard rate but received in-home displays that alerted its members of critical peak periods. The sample size for each group was designed and selected to be representative of each type for the whole system. SVE

1. He estimates an electricity demand model for Japanese consumers that face Time-of-Day (TOD) rates, where peak hours are 7:00 AM to 11:00 PM every day, using a sample of 371 households in the summer of 2003. He finds that the impact of TOD rates on peak time consumption not only depends on the price effect, but also on the self-selection effect particularly for households that own non-electric water heaters.

2. As one referee indicated to us, CPP rates are designed to be revenue neutral for the average customer. Such customers' bills are unaffected if they fail to shift their CPP period consumption to non-CPP periods. However, customers with above average use during CPP periods can experience increases in their total bills if they fail to shift some of the CPP period consumption from CPP to non-CPP periods.

3. However, PTR has its own shortcomings. For example, potential inaccuracies in baseline (pre-rebate use) estimates can lead to distorted rebates.

set the CPP energy rate during critical peak times to be about five times greater than the standard energy rate. As an offset, the energy rate for all CPP participants was reduced during all non-critical peak times.

We begin our examination of this experimental CPP program by providing a literature review of dynamic pricing and its impact on energy use in section 2. In section 3, we discuss the design of SVE's pilot program in detail, and provide variable definition and data sources in section 4. We detail our modeling approach, model estimates and demand impacts in section 5.

As we indicate in section 5, we evaluate two main aspects of the pilot using separate econometric techniques. First, we ascertain the average demand impact of CPP pricing on each test group, using a constant elasticity of substitution (CES) demand system and fixed effects models. Second, by using survey questions regarding "green" attitudes and other customer attributes, we determine some of the main reasons for the different reactions to CPP pricing among individual participants. Findings from this step may help SVE to optimize its recruitment efforts when expanding this program to other households.

2. LITERATURE REVIEW

Dynamic pricing, which requires advanced metering infrastructure, is mainly used to better align electricity cost with price along the time-scale continuum. For instance, the cost of generating and delivering electricity during periods of high demand or peak-load, such as during hot summer days where air-conditioning (AC) saturation is extensive, is higher than during other periods. Dynamic pricing permits the use of time-varying tariffs to reflect such cost variation, and often results in load shifting from high or peak demand periods to off-peak periods. The extent to which dynamic pricing (or other demand-response programs) contributes to load shifting/reduction is currently of great interest to utilities. This is because they are interested in: Comparisons of the effectiveness of traditional demand response programs, such as direct load control (DLC) and time-of-use (TOU) pricing, with those of dynamic pricing programs; designing effective load shifting or demand response programs as part of larger regulatory, reliability, environmental and efficiency goals; and enabling cost efficient provision of power through avoided capacity, energy and transmission and distribution (T&D) costs.

A starting point for studies that explore the load impact of dynamic pricing is an exposition of the conditions that necessitate such pricing. In their 1995 survey of the theory of peak-load pricing, Crew et al. provide a succinct explanation of these conditions. Primary among these are commodities that are not economically storable and for which demand varies over time—e.g. electricity. If prices do not increase during high demand periods for these goods, it is necessary to install capacity to meet the spike in demand, which will remain idle during off-peak periods. Peak-load pricing mitigates the inefficiency resulting from idle excess capacity by reducing demand at peak times.

Time-of-use (TOU) prices are one form of peak-load prices that are designed to accomplish this goal. TOU prices are fixed months in advanced for blocks of time, such as peak, off-peak, or "shoulder months," but do not reflect price variations within blocks that result from short-term demand and supply conditions (e.g., an unseasonal spike in temperature). Critical peak prices (CPP) are a response to the shortcomings of TOU prices. They are made possible with the evolution of metering technology that enables more flexible customer response to time-varying prices. While CPP prices sometimes retain the block-varying price feature of TOU rates, they also incorporate charges at critical system peaks. They are, however, still somewhat inflexible, because their ability to reflect more current market conditions is limited. Real-time pricing (RTP) overcomes these limitations by allowing prices to truly reflect current market conditions.[4]

Several studies have explored the load impact of peak-load pricing. Aubin et al. (1995) discuss the French state-owned electric utility EDF's real-time pricing experiment. They report a 27% demand reduction in red alert peak hours where the tariff was 17 times greater than the least expensive period's tariff. Baladi et al. (1998) investigate residential consumer response to voluntary TOU rates using experimental data from Midwest Power Systems of Iowa. They find that TOU pricing, where the peak period price was set to be 4.6 times the off-peak period price, resulted in 20% reduction in peak usage relative to baseline use. Borenstein et al. (2002) present the case of Gulf Power's Residential Service Variable Price (RSVP) option, which set a critical period rate that was three times greater than the regular peak price. Results from this program indicate average energy reductions of 41% during critical periods. Faruqui and George (2005) present results from the Statewide Pricing Pilot (SPP) approved by the California Public Utilities Commission (CPUC). In general, for TOU prices that were 70% higher than the standard rate, residential peak use reductions were roughly 5%. For CPP prices that were 5 to 10 times as high, residential peak use reductions were roughly 8–15% and 25–30% with smart thermostats.[5]

More recent studies provide similar findings. Williamson and Shishido (2012) present the Smart Study Together pilot ran by Oklahoma Gas & Electric (OGE). The program involved TOU-CPP and Variable Peak Pricing (VPP)-CPP rates with the CPP rates set at about 10 times the off-peak rates. Average peak demand reductions were 20% (0.73 kW) and 21% (0.75 kW) for those on the TOU-CPP and VPP-CPP rates, respectively. Faruqui and Sergici (2011) present results from the dynamic pricing experiment of Baltimore Gas & Electric (BGE). They find critical peak reductions, where peak period prices were 8–10 times higher than off-peak period prices, were 18% without enabling technologies, 23% with Energy Orbs, and 33% with Energy Orbs and smart thermostats. Herter (2012) presents results from a Sacramento Municipal Utility District (SMUD) Residential Summer Solutions Study. The dynamic pricing option featured a TOU-CPP rate where the CPP rate was about 7 times the off-peak rate. The CPP treatment group reduced its average critical peak demand by 53 percent during the summer. This is one of the strongest reductions registered among the studies that we have examined.

Faruqui and Sergici (2010) survey 15 time-varying pricing experiments and programs for electricity and find that households respond to higher prices by reducing demand. The amount of reduction depends on the extent of the price increase, AC ownership and the presence of enabling technologies such as programmable thermostats. In general, peak demand reductions range from 3% to 6% for TOU rates, 12% to 22% for CPP rates with no enabling technology, and 26% to 50% for CPP rates with smart thermostats.[6]

4. Using a simulation model of a competitive generation market, Borenstein (2005) finds that real-time pricing (RTP) reduces peak demand, peak electricity production and the use of low capital/high variable cost peaking units; during the highest demand periods, market equilibrium is reached through higher prices rather than the use of additional generation capacity.

5. There are also studies that have examined demand reductions by large load customers. Braithwait & O'Sheasy (2002) provide evidence of substantial demand response by industrial and commercial customers to an hourly pricing (RTP) program ran by Georgia Power Company (GPC). They find that load reduction by industrial customers ranged from 30–60% during high hourly price periods ($0.50/kWh to $1.50/kWh). Commercial customers reduced demand by 10% to 25% in response to similar price increases. Goldman et al. (2004) also report comparable peak time demand reduction by 32 Niagara Mohawk Power Corp (NMPC) large load customers of who faced RTP in the years 2000–2002.

6. The survey also indicates that price elasticities of demand range from −0.02 to −0.10, and substitution elasticities from 0.07 to 0.40.

A survey, summarized in Table 1, from various time-varying pricing programs in Faruqui and Wood (2008) also indicates similar findings.

3. SVE PILOT DESIGN

SVE elected to run the program from June to August in 2011[7] and set a maximum of 35 CPP events for the season.[8] It also set CPP events to be between 4 to 8 PM on weekdays; these are for hours starting at 16 to 19. In addition, it indicated that participants would receive day-ahead notification via four methods of communication: Email, text message, phone calls using IVR (Integrated Voice Response), and in-home display. As part of the project, the in-home displays and/or smart thermostats were purchased for the test group participants.

SVE has two separate residential rate classes (Residential and Farm-Rural). Once the program rules were set, SVE opted to use a stratified random selection protocol, described below, to select participants from residential and rural residential customers with smart meters. A total of three test groups were established for each residential rate class.

Group one participants, randomly selected from the sample, were provided CPP price signals (time and duration of an event) via one or more of the four technologies (chosen by the participant) outlined above. Selected members could opt-out of the program if they wished; approximately 2.5% of participants opted out of the program. In addition, since their bills reflected the lesser of the CPP or the standard rate, they faced a no-lose proposition.

Group two is made up of those recruited to participate from the remaining residential and rural residential customers who have AMI meters. The recruitment effort utilized various marketing tools, such as flyers and bill inserts, to gain enough participants to have a statistically valid sample size. Similar to the randomly selected opt-out group members, these opt-in participants were able to choose the mode of communication they preferred. Group two participants were not offered the bill protection that Group one enjoyed.

Group three members were also randomly selected from the remaining residential and rural residential members with AMI meters. Members of this group received the same information via an in home-display; however, they remained on the standard rate. This tests the impact of providing critical peak event information without the pricing structure. It permits the identification of usage reductions (or alterations) by households that are possible without price incentives.

The sample size selection process aimed at creating statistically representative groups that reflect SVE's system with a 5 percent sampling error at a 95 percent confidence level. It relied on stratified random sampling to accomplish this where representative samples for each test group were drawn from different brackets of customers with AMI. Stratified random sampling was chosen because it permits more efficient sampling; a smaller representative sample can be drawn at the same level of precision as simple random sampling using this method. The number of brackets and their boundaries are determined via the "Dalenius-Hodges" method, which is a well-known statistical technique that draws sample boundaries on the basis of the frequency distribution of the selected stratification criterion.[9] In this case, the criterion was energy use per customer. The total

7. SVE ran the CPP program over the summer because its power supplier, Basin Electric, already has an extensive electric heat direct load control program that affords it substantial control over the winter peak and makes that period's peak below the summer peak.

8. The number of possible CPP days was unusually high at 35 because the CPP rate was designed to be revenue neutral at energy use duration of 140 hours or 35 days. However, only 13 CPP days were called during the summer.

9. Dalenius and Hodges (1959).

Table 1: Results from Two Surveys on the Effect of Time-Varying Prices

program	year(s)	participants	price design	price ratio (CPP-TOU peak/off peak) [1]	critical peak reductions [2]
PSE&G Residential Pilot Program	2006/7	1,286	TOU-CPP	7.67 (2006) 15.7 (2007)	14% (no Tech) 26% (w/SMT)
OEB Smart Price Pilot	2006/7	373	TOU CPR CPP	3 (TOU) 8.6 (CPR) 9.7 (CPP)	6% (TOU) 18% (CPR) 25% (CPP)
Anaheim CPP experiment	2005	123	CPR	3.18 – 5.19	12%
Idaho Residential Pilot	2005/6	505 423	TOU CPP	1.8 (TOU) 3.7 (CPP)	0% (TOU) 50% (CPP w/SMT)
Energy Australia Strategic Pricing Study	2005	1,300	DPP	25–33 (DPP_H) 13–17 (DPP_M)	25% (DPP_H w/IHD) 20% (DPP_M w/HD)
Ameren UE	2004/5	545	TOU-CPP	6.25	13% (no Tech) 30% (w/SMT)
California Automated Demand Response Pilot	2004/5	171 (2004) 131 (2005)	TOU-CPP	9	21% (avg daily kWh < 24 w/SMT) 47% (avg daily kWh > 24 w/SMT)
California Statewide Pricing Pilot	2003/4	2,500	TOU CPP-F CPP-V	2 (TOU) 3 (CPP-F) 9 (CPP-V)	0–6% (TOU) 13% (CPP-F) 16% (some SMT) 27% (w/tech
The Gulf Power Select Program	2000/1	2,300	CPP	8.3	41% (w/SMT)
BGE's Smart Energy Pricing Pilot	2008	1,375	DPP PTR	DPP = $1.30 PTRH = $1.75 PTRL = $1.16	18–21% (no tech) 23–27% (w/IHD) 28–33% (w/IHD & SMT)
CPL's Plan-it Wise Energy Pilot	2009	1,251	TOU CPP PTR	TOU = $0.34/ $0.27 PTP = $1.80/ $0.85 PTR = $1.60/ $0.65	3% (TOU) 18% (PTR) 23% (PTP)
PEPCO's PowerCentsDC Pilot	2008	1,300	CPP CPR HP	CPP = $0.75 CPR = $0.75 HP = PJM wholesale price	13% for high income 11% for low income
PGE's full-scale program	2008/9	25,000	incremental CPP (ICPP)	ICPP = $0.60	23% high income 9% low income

[1] The last four are peak period rates ($/per kWh).
[2] IHD is in-home display and SMT is smart thermostat.
[3] DPP (dynamic peak pricing) is another term for CPP and CPR (critical peak rebate) is another term for PTR.

Table 2: Response Rate to Enrollment Survey by Test Group

Sample	Test Group	Surveys Sent	Surveys Returned	Response Rates
Residential	Opt-out	98	45	46%
	Opt-in	34	28	82%
	Tech Only	96	26	27%
Farm and Rural Residential	Opt-out	165	77	47%
	Opt-in	42	37	88%
	Tech Only	161	41	25%
Total		596	272	46%

sample size for each stratum, or bracket, was then determined by the "Neyman" allocation method, which uses the percent standard deviation of each stratum to the total to determine the optimum number of sampling units.[10]

This pilot included an enrollment survey as well as a post-pilot survey. The focus of the enrollment survey was to identify household and respondent characteristics that may impact household energy consumption and program reaction, such as the presence of central air conditioning in the home or attitudes about environmental issues. The post-pilot survey focused on the respondents' level of satisfaction with the program in order to refine future deployments.

Key components of the enrollment survey included questions on:

- Presence of various household appliances that influence energy use, including central air conditioning.
- Willingness to accept and incorporate technological advancement into daily life.
- Topics that identify the household members' attitudes on the environment and actions taken based on this attitude.

Each test group participant was surveyed, and response rates are listed in Table 2.

We should note that the minimum sample sizes required to achieve a statistically valid representation of the population are a fraction of the numbers used in the CPP pilot. This is because an enrollment survey is a critical part of the pilot program and in an effort to ensure reliable, significant, and robust results, this minimum is raised to levels beyond those required to achieve a representative sample. In particular, the minimum thresholds for the samples are escalated based on an assumption of a 25 percent response rate to the survey for each test group. In addition to the assumed low enrollment survey response rate, this escalation helped to account for bad data and other unforeseen factors. Therefore, survey response rates beyond 25% permit us to make valid inferences about the population which the pilot samples are designed to represent.

4. VARIABLE DEFINITIONS AND DATA SOURCES

As indicated earlier, the CPP experiment involves households from residential and farm-rural rate classes, and three test groups for each rate class. Their energy usage is recorded bi-hourly over the months of June, July and August in 2011; we aggregate these to the hour level and use hourly data in our analysis. During these months there were 13 CPP event days called.

10. See Neyman (1938).

Table 3: Summary Statistics of Fixed Effects Regression Variables

variables	units	Avg	Max	Min	Stdev	N
Demand (Residential)	kW	1.94	39.12	0.00	1.83	713,314
Cooling-degree Hour (Residential)	°F	8.68	34.00	0.00	7.82	713,314
Dew Point (Residential)	°F	62.39	81.00	38.00	7.81	713,314
Demand (Rural)	kW	3.99	130.91	0	5.25	1,185,582
Cooling-degree Hour (Rural)	°F	8.67	34	0	7.82	1,185,582
Dew Point (Rural)	°F	62.38	81	38	7.81	1,185,582

In addition, hourly cooling and heating degree data for the cooperative's service territory is gathered from the Midwestern Regional Climate Center (MACS). MACS provides such data for various weather stations, which are mapped to the service territory of the cooperative. Summary statistics of the data used in the study are provided in Table 3.

The information gathered from the pre-pilot survey is used to understand participants' characteristics, and identify, with econometric modeling, which demographics and features drive program responses. The main characteristics that we use in our demand response assessment from the survey include ownership of central air conditioning units[11] and "green attitudes." We construct the green attitude variable using the enrollment survey responses to four general categories of questions about the environment from test group participants. These categories deal with:

- A participant's stated level of concern about climate change;
- Demonstrated behavior personally taken to act on the stated concern;
- Stated attitude about others' actions to address climate change; and
- Stated level of favorability about organizations seeking to reduce man-made greenhouse gas emissions.

We examine each respondent's answers to questions in these four areas to create a green attitude variable. The "green" attitude variable is a composite index, which ranges from 0 to 1, of responses to ten different attitudinal questions. Responses to these questions are coded such that the greater the level of "green" attitude the higher the score. In particular, responses to the questions are coded as follows:

Missing Response:	0 = 0.0
Strongly disagree:	1 = 0.2
Somewhat disagree:	2 = 0.4
Unsure:	3 = 0.6
Somewhat agree:	4 = 0.8
Strongly agree:	5 = 1.0

We assume some questions are better representations of a "green" attitude than others. Thus, responses are weighted to reflect their relative importance when constructing the index. In particular,

11. The amount of electricity use depends on many different appliances in customer households. Three primary appliances that typically drive electricity use during peak times are central air conditioning (CAC), electric water heaters and electric ranges/ovens. We tested the influence of these appliances, but only CAC is found to have a statistically meaningful effect on hourly demand.

Table 4: Green Attitude Variable Values Across Groups

		Residential Class	Farm-Rural Class
	Average	**0.63**	**0.65**
Opt-out	Min	0.00	0.00
	Max	0.98	0.95
	Average	**0.71**	**0.64**
Opt-in	Min	0.00	0.00
	Max	0.96	0.89
	Average	**0.75**	**0.60**
Tech Only	Min	0.00	0.86
	Max	0.99	0.00

high indicators of a "green" attitude are weighted highly in the index (weight = 0.15), medium indicators are weighed in the middle (weight = 0.10), while low attitude indicators are given a low weight (weight = 0.05). We present the questions and the weights used to construct the index in Table A1 in the Appendix.

Table 4 presents summary statistics of the values of this variable by rate class and test group.

5. MODELING PROCEDURE

5.1 Estimation Approach

While our focus in this paper is the extent of demand reduction from the CPP experiment, which we estimate by using fixed effects models detailed below, we also estimate demand functions for power use to examine price and substitution elasticities. We use the CES demand system, expressed in logs, to estimate price and substitution elasticities as detailed in Faruqui & Sergici (2010). The CES function used to estimate substitution elasticity is theoretically and practically appealing and permits us to model peak to off-peak demand as a function of peak to off-peak prices and weather, and individual effects. Since we have hourly data for each month by customer, we are able to determine the marginal price paid by each customer in each month for each 500 kWh block and pricing period as defined in the CPP pilot based on the rates provided in Table 5.

The general form of the CES model used to estimate substitution elasticity is given by:

$$ln\left(\frac{D_{p,it}}{D_{op,it}}\right) = \sum_{i=1}^{N} \alpha_i + \sigma * \ln\left(\frac{P_{p,it}}{P_{op,it}}\right) + \delta * (CDH_{p,it} - CDH_{op,it}) + \varepsilon_{it} \quad (1)$$

The left hand side term is the natural log of CPP period to non-CPP period demand for the *ith* individual during day t; the first term on the right hand side is the sum of individual specific intercept terms (α_i, $i = 1 \ldots N$); the second term is substitution elasticity (σ) times the natural log of CPP period to non-CPP period price; the third term is a measure of weather effect (δ) times the difference in CPP period to non-CPP period cooling degree hours; and the last term is random noise. Cooling degree hours are not logged since there are observations with values of zero.

The CPP period variables are averages of energy use, price and CDH during CPP hours per day while their non-CPP counterparts are averages for the non-CPP hours per day. For example, $D_{p,it}$ is individual i's average hourly demand during CPP hours in day t while $D_{op,it}$ is the same individual's average hourly demand during non-CPP hours in day t. The data set up in this manner

Table 5: Rate Structure by Classes

	Residential		Farm-Rural	
Usage Ranges	Default rate	CPP rate	Default rate	CPP rate
$0<\text{kWh}<=500$	\$0.0915	\$0.0689	\$0.1038	\$0.0781
$500<\text{kWh}<1000$	\$0.0746	\$0.0562	\$0.0915	\$0.0689
>1000 kWh	\$0.0746	\$0.0562	\$0.0746	\$0.0562
Critical Peak kWh		\$0.5000		\$0.5000

consist of 328 cross-sections or individuals with 91 daily observations for the residential class and 546 cross-sections with 91 daily observations for the farm-rural class.

In addition, we also obtain daily price elasticity of demand by using the following model:

$$ln(D_{it}) = \sum_{i=1}^{N} \alpha_i + \beta * \ln(P_{it}) + \theta * CDH_{it} + \varepsilon_{it} \tag{2}$$

This model is estimated using average daily per hour values, where D_{it} is individual i's average daily demand per hour, and P_{it} and CDH_{it} are price and cooling-degree values for the same time period. This model is also based on 328 cross-sections with 91 average daily observations for the residential and 546 cross-sections with 91 daily observations for the farm-rural class. We estimate both models (Model 1 and Model 2, respectively) using fixed effects.

We also use a variation of the difference-in-differences method to estimate the effect of the CPP experiment on critical peak period demand. Since the introduction of this method by Ashenfelter and Card (1985), it has become a popular approach to estimate the effect of various program interventions for which treatment and control groups exist. In the most common set up, two groups are observed at different points in time, where group one receives treatment in the second period and group two does not. The behavior of the second group is used as baseline against which the effect of the treatment on the first group is measured.

However, due to the special set up of our experiment where the opt-out group receives bill protection and members of the opt-in group self-select into the program, we do not compare test groups' energy use relative to the control group. Instead we use the non-CPP period use of each test group as its baseline. We compare treatment or critical peak period price signal effects relative to this baseline. An example of this approach is in Herter and Wayland (2010).

To illustrate how this modified method works, we consider a simple set up, where members of a test group T receive treatment (TE) during certain periods. We can specify this model as follows:

$$y_{it,T} = \alpha_i + \beta_{t,T} * d_{t,T} + \gamma_{t,T} * TE + \varepsilon_{it,T} \tag{3}$$

where $y_{it,T}$ is the outcome that we observe from the experiment; α_i is an individual specific intercept term; $d_{t,T}$ is a dummy variable for period t and test group T; $\beta_{t,T}$ is the parameter that captures group T's outcome during period t; TE is a dummy variable that takes the value of one when the treatment is in effect and 0 otherwise; $\gamma_{t,T}$ is the parameter that captures the outcome of the treatment; and ε_{it} is a random noise term. The outcomes in the non-treatment and treatment periods, respectively, are estimated by:

$$y_{it,T} = \hat{\alpha}_i + \hat{\beta}_{t,T} * d_{t,T} \tag{4}$$

Table 6: Test Group Types by Rate Class

	Rate Class or Household Type	
Test Group Type	residential	farm-rural
Opt-out (involuntary)	IRS	IFR
Opt-in (voluntary)	VRS	VFR
Tech Only (IHD)	TRS	TFR

$$y_{it,T} = \hat{\alpha}_i + \hat{\beta}_{t,T} * d_{t,T} + \hat{\gamma}_{t,T} \tag{5}$$

The estimate that measures the effect of the treatment on group T is given by:

$$\Delta y_T = (\hat{\alpha}_i + \hat{\beta}_{t,T} * d_{t,T} + \hat{\gamma}_{t,T}) - (\hat{\alpha}_i + \hat{\beta}_{t,T} * d_{t,T}) = \hat{\gamma}_{t,T} \tag{6}$$

Therefore, the parameter estimate on the term with the treatment dummy captures the treatment effect. Based on this general framework, we specify energy demand as a function of:

- Individual specific effects,
- Hour of the day for the opt-in, opt-out and technology groups,
- Event day hours for all three test groups,
- Cooling-degree hour (CDH) times hour of the day for the three test groups,
- CDH times event day hours for all three test groups,
- Dew point (DP) times hour of the day for all three test groups,
- DP times event day hours for all three test groups

This demand model is estimated using fixed effects.

We also estimate a set of models that specify demand as a function of household characteristics gathered from the enrollment survey discussed earlier. Although some of these variables are time invariant, they are interacted with hourly variables in the models permitting the use of FE estimation. The household characteristics fixed effects models are based on a subset of the above households that received and responded to the pre-pilot survey. These set of models feature not only separate functions by rate class, but also by test group. Each model is specified as a function of:

- Individual specific effects,
- Cooling degree-hour (CDH),
- Dew Point (DP),
- Hour of the day dummy variables,
- Dummy variables for event day hours,
- Hour of the day for households with central air conditioning (CAC),
- Event day hours for households with CAC,
- Hour of the day for different levels of "green" attitude (pctgn),
- Event day hours for different levels of pctgn,

Table 6 provides a matrix of the test groups and rate class/household types used in modeling.

Table 7: CES System Estimates

Model	Rural Model 1		Residential Model 1		Rural Model 2		Residential Model 2	
Estimator	FE		FE		FE		FE	
Cross Sections	546		328		546		328	
Time Series Length	91		91		91		91	
R-square	0.846		0.770		0.259		0.219	
Variables	**Parameter Estimates**	**Pr>|t|**	**Parameter Estimates**	**Pr>|t|**	**Parameter Estimates**	**Pr>|t|**	**Parameter Estimates**	**Pr>|t|**
lnP	−0.138	0.000	−0.139	0.000				
CDH	0.026	0.000	0.038	0.000				
ln(Pp/Pop)					−0.061	0.000	−0.088	0.000
CDHp-CDHop					0.015	0.000	0.026	0.000

Table 8: Summary of Elasticity Estimates from Different Programs

Jurisdiction	Pilot	Year	program	sub elasticity	price elasticity
CA	Statewide Pricing Pilot	2003–2004	CPP-F/CPP-V	0.09 to 0.15	−0.03 to −0.05
France	Électricité de France Tempo Program	1996	day-of-year		−0.79
IL	Energy-Smart Pricing Plan	2005	RTP		−0.05 to −0.07
NJ	GPU Pilot	1997	CPP	0.30	
NJ	PSE&G Residential Pilot Program	2006–2007	CPP	0.06 to 0.13	
NSW	Energy Australia's Network Tariff Reform	2006	TOU		−0.30 to −0.38
Summary				**0.06 to 0.30**	**−0.03 to −0.79**

5.2 Model Results

Table 7 provides the results from the CES demand models, where individual specific parameter estimates have been suppressed to conserve space. We find substitution elasticities of 0.06 and 0.09 for the rural and residential households, and price elasticities of −0.14 for both rate classes.

These values are within ranges reported in other studies. King and Chatterjee (2003) summarize estimates of own-price and substitution elasticities for time-of-use and critical peak pricing experiments presented in 56 papers published since 1980. They find short run own-price elasticities range from a low of −0.13 to a high of −0.34 in forty-nine U.S. experiments, and from −0.28 to −0.66 in seven other industrialized countries' experiments. They also find substitution elasticities range from 0.10 to 0.19 for fourteen U.S. experiments. On the other hand, in their survey of 15 dynamic pricing experiments and programs for electricity, Faruqui and Sergici (2010) find that price elasticities of demand range from −0.02 to −0.10. They also find substitution elasticities range from 0.07 to 0.40. Other studies, as summarized in Table 8, find price and substitution elasticity estimates that are within the high and low ranges presented in these two studies.

In addition, using average values of CPP period to non-CPP period prices we can determine the extent of average CPP to non-CPP period demand reductions based on our CES parameter estimates. For those receiving the CPP treatment in the farm-rural rate class the average demand shift from CPP to non-CPP period is 12%. On average, this value is 18% for treatment recipients in the residential rate class. Next, we examine if we can find similar demand savings based on our fixed demand models.

The farm-rural demand model is based on 371 cross-sections or program participants with an average hourly reading of 2,178. Of the 371 cross-sections 168 are opt-out customers, 43 are opt-in, and 160 are those with in-home displays only. Since the hourly readings vary across participants, we have an unbalanced panel data with 802,636 observations. The residential demand model we estimate has 230 cross-sections with an average time-series length of 2,178 hourly data. Of the 230 cross-sections 99 are opt-out customers, 34 are opt-in, and 97 are those with in-home displays only. The total number of observations in this rate class we use in the model is 499,908.

Estimates from the fixed effects farm-rural and residential household demand models are presented in Table A2 in the Appendix. Note that we have suppressed the household effect estimates and present estimates for hours 13 to 22 to save space; as stated earlier the CPP period was for hours starting at 16 to 19. Our models capture the kW impact of the CPP price signal by comparing each test group's non-CPP load to its CPP load profile. The models also control for weather differences during CPP and non-CPP days. We note from the model estimates that the kW impact of weather during event hours is not significantly different from non-event hours; most of the parameter estimates of the hourly cooling-degree and dew point variables are not statistically significantly different from zero during event hours whereas the effect of hourly cooling-degrees and dew point are positive and significant during most non-event hours. Nonetheless, the kW impact of CPP takes into account the weather impact during CPP hours along with event hour dummy parameter estimates.

Figures 1 and 2 present the hourly load profiles during event and non-event days.

We note that the farm-rural test groups' power consumption is generally higher during pre-treatment hours on event days relative to non-event days. Consumption during pre-treatment hours on event days, however, is not much different from such consumption on non-event days for the residential test groups. Therefore, there appears to be some "pre-cooling" and higher power use before event hours among farm-rural households, but not among residential households. In addition, all test groups ramp up consumption after the event hours.

We also estimate separate fixed effects models for each rate class and test group based on household attributes that we construct from the pre-enrollment survey. For the farm-rural rate group we estimate separate models for the opt-out (95 cross-sections), opt-in (42 cross-sections), and in-home display (55 cross-sections) groups. Similarly, for the residential class we estimate demand models for: the opt-out test group, with 32 cross-sections; the opt-in test group, with 21 cross-sections; and the in-home display group, with 25 cross-sections. Each of these six groups has 2178 hourly observations.

We present these results in Table A3 in the Appendix. In general, those with CAC use more energy relative to those without CAC during non-event hours. In addition, energy use is lower during event days relative to non-event days, and those with greater "green" attitudes use less energy on all days (non-event and event days) relative to those with less "green" attitudes. The effect of "green" attitudes on demand reduction is greatest for the in-home display test groups. In addition, the higher the level of cooling-degree hours and dew point, the higher is demand for energy. As in the first set of models, weather effects on demand are not statistically different during event and non-event days. Therefore, we do not specify models that feature such differences.

Figure 1: Farm-Rural Load Shapes by Test Group for during Event and Non-Event Hours

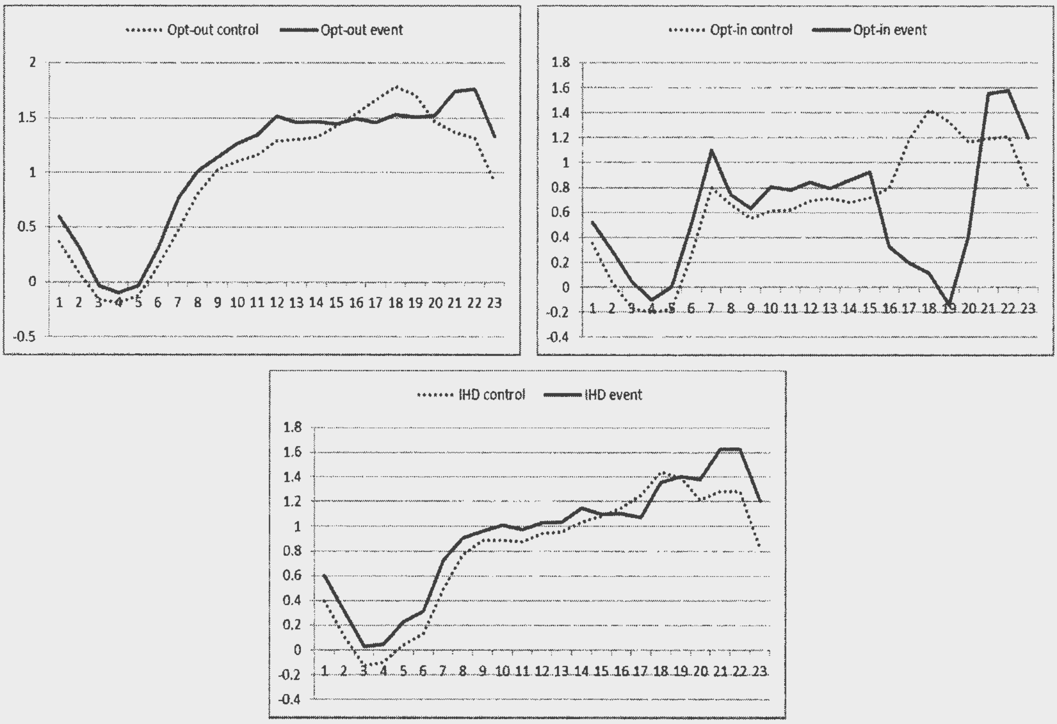


Figure 2: Residential Load Shapes by Test Group during Event and Non-Event Hours

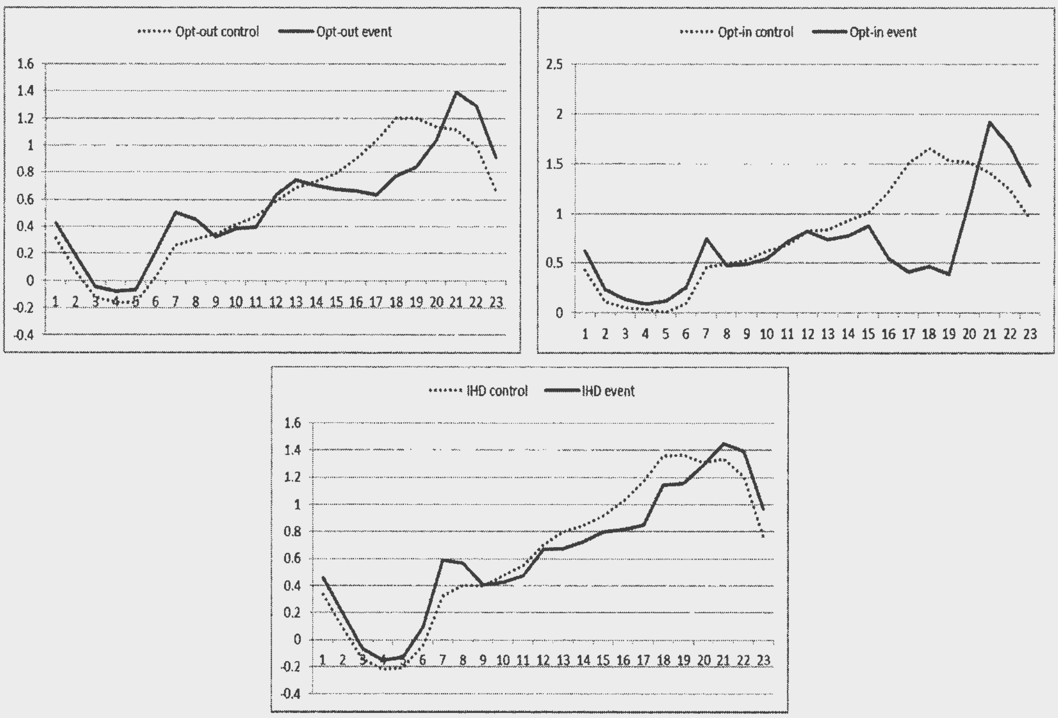
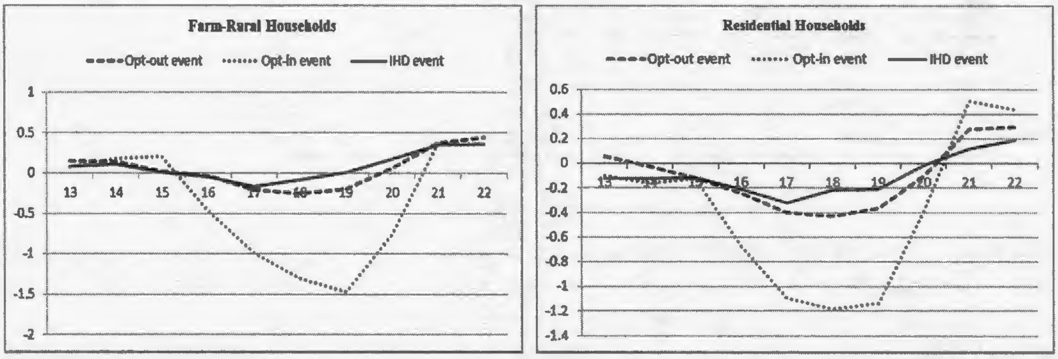


Table 9: Average Impact Estimates from Fixed-Effects Demand Models

Test Group	Baseline kW	kW Impact	% impact	95% confidence interval	
Farm Rural					
Opt-out	5.22	−0.17	3%	0.07	−0.42
Opt-in	3.78	−1.06	28%	−0.50	−1.62
IHD	5.23	−0.07	1%	0.08	−0.23
Residential					
Opt-out	3.16	−0.36	11%	−0.17	−0.55
Opt-in	3.90	−1.02	26%	−0.70	−1.35
IHD	3.36	−0.24	7%	−0.05	−0.43

Figure 3: Average Demand Impact by Hour for the Farm-Rural and Residential Households



5.3 Peak Period Demand Changes

We provide summaries of the change in demand during critical peak period in Table 9. The numbers given provide the average hourly reduction both in kW and percentage terms. The results indicate that members who are in the opt-in test group had the highest level of reduction during the peak period. Of the two opt-in test groups, those in the farm-rural rate class reduced their usage the most; on average, their use declined by 1.06 kW or 28% during the critical peak hours. On average, the farm-rural and residential treatment groups reduce demand by 11% and 15%, respectively. These values are in line with those estimated from the CES models, which are 12% and 18%, respectively, as noted in section 5.2.

We use the delta method to develop 95% confidence bounds for the average kW impacts for each test group. Except for the farm-rural opt-out and in-home display (technology only) groups, the CPP program has resulted in tangible peak load savings. In addition, it appears that allowing customers to opt-in to these sorts of programs hold the greatest promise in terms of peak demand reductions.

Figure 3 presents the average demand impacts by hour for each rate class and test group. Note that the four critical peak hours begin with hour 16 and end after hour 19.

5.4 Household Characteristics Demand Model Results

We consider both structural (appliance stock, building vintage, number of people in a households, age of participants) and attitudinal (preference for new products, and willingness to act

Table 10: Average Impact Estimates by Household Characteristics

	Total	CAC	Green	General
Farm Rural				
Opt-out	−0.06	0.21	−0.56	0.30
Opt-in	−0.96	−0.05	−0.21	−0.70
IHD	−0.06	0.09	−0.55	0.40
Residential				
Opt-out	−0.31	0.15	−0.13	−0.33
Opt-in	−1.10	−0.61	0.38	−0.87
IHD	−0.02	−0.60	−1.49	2.07

Table 11: Average Impact Estimates from Fixed Effects Models

	Farm Rural (kW Impact)			Residential (kW Impact)		
Model Type	Opt-out	Opt-in	IHD	Opt-out	Opt-in	IHD
Minimum Green w/CAC	0.51	−0.74	0.49	−0.18	−1.48	1.47
Average Green w/CAC	−0.06	−0.96	−0.06	−0.31	−1.10	−0.02
Maximum Green w/CAC	−0.32	−1.04	−0.30	−0.39	−0.97	−0.50
Difference in Max to Min Green	**−0.82**	**−0.30**	**−0.79**	**−0.21**	**0.52**	**−1.97**

on concern about the environment) characteristics to identify the elements that contribute to critical period demand reduction. While the results from the survey potentially permit the testing of numerous structural and attitudinal models, our findings indicate the presence of central air conditioning (CAC) and green attitude contribute most to changes in behavior during event hours. Hence, we focus our research on these drivers of event period usage.

In general, we find that the higher a customer's green attitude, the greater its energy reduction, regardless of other household characteristics. Green attitude, and not electric appliance presence, is the greatest driver of reduction in household energy use during peak events. We present a summary of average impacts by household characteristics in Table 10 to demonstrate this. On average, only for two test groups (residential opt-in and in-home display) does the presence of CAC lead to demand reduction during CPP periods.

The residential opt-in and both opt-out groups reduce demand during CPP hours for reasons other than CAC ownership and green attitudes. Both in-home display groups and the rural opt-out group increase power use net of CAC ownership and green attitude-related reductions. Such increases mute their overall response during CPP hours. These are the groups that register either low or statistically insignificant demand reductions.

We note, however, that while we find a significant correlation between demand reduction and green attitudes, such an attitude does not appear to lead to extra demand reduction among those in the residential opt-in group. The positive coefficients of the green variables for this test group indicate the flattening or moderation of the decline in demand during CPP hours. This may be due to the self-selection of customers whose behavior already matches the desired response.

In addition, households with CAC units that reduce usage during peak events do so at a greater level if they have an above average green attitude. The summary of the effect of the combination of CAC ownership with green attitudes is presented in Table 11. The table shows how demand impact changes over different levels of green attitudes when the household has an AC unit available. Across all programs, the maximum green household is expected to reduce demand by 0.59 kW more than a household with the minimum green attitude; this value is the average of the difference between maximum green with AC demand impact and minimum green with AC demand impact. We also note that the residential opt-in group is the only test group where increasing "green" attitudes do not afford more kW savings.

In general, CPP price signals lead to peak demand reductions. Central air conditioning ownership contributes to this decline, though less than the level of green attitude, which contributes to such reduction significantly. In addition, other factors unrelated to greenness and the presence of CAC also contribute to peak period demand reductions: especially among the treatment groups, but not for the in-home display groups, which have the weakest overall response.

6. CONCLUDING REMARKS

Our survey of various time-varying programs and experiments shows that they have, on average, led to 16%, 25% and 34% reduction in peak time use without enabling technologies, with some form of in-home display and with smart thermostats, respectively; in-home displays make an incremental peak demand reduction of about 9% possible while smart thermostats make additional reduction of about 18% possible. Therefore, peak time energy use reduction of about 25%, or higher with enabling technologies, appears to be the norm.

For the SVE CPP pilot, we find that the average of the rural and residential opt-in test groups' peak time reduction is 27% and those of the opt-out test groups' is 7%. Since most of the survey results are based on opt-out time-varying prices, our results are about half to a third of those reported in similar programs. We deduce that offering CPP rates on an opt-out basis with bill protection leads to significantly lower per-participant peak demand reduction. The per-participant kW reductions are 1.04 and 0.27 for the opt-in and opt-out programs, respectively. Since there are more participants in the opt-out (267 from both rate classes) than in the opt-in (77 from both rate classes) program the difference in peak demand reductions at the program-level are not as large. For the opt-in group, program-level peak demand reduction is 80 kW while it is 72 kW for the opt-out group. Bill protection is generally offered to ensure customer buy-in. Our results indicate that efforts should be made to emphasize that customers have the choice to switch from the CPP rate to the standard rate when deploying such programs rather than offering bill protection. This approach is likely to garner greater demand reduction.

Offering the program on an opt-in basis does result in significant kW reduction during critical peak events. However, based on our study of household characteristics that drive peak demand reductions, those that self-select into the program do not offer any more demand reduction than would be achieved if the CPP rate were offered as the default. Most customers that self-select into such programs already have strong incentives to reduce peak demand, as captured by the positive coefficient of the characteristic that drives such reductions the most ("green" attitude). Therefore, we recommend exploring the effect of offering CPP rates on an opt-out basis and without bill protection to fully understand the demand changes that are possible under this pricing scheme.

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APPENDIX

Table A1: Questions and Weights of "Green" Attitude Index

Question	Weight in Index	Survey questions used to gauge "green" attitudes
1	0.15	The long term threat from global warming/global climate change is serious.
2	0.15	I trust environmental organizations, such as the Sierra Club or Greenpeace, to give me dependable information on how to optimize my energy use.
3	0.05	I trust academic or scientific organizations, such as researchers at a major University, to give me dependable information on how to optimize my energy use.
4	0.05	I trust government/public sources, such as the Department of Energy or my local municipality, to give me information on how to optimize my energy use.
5	0.10	Everyone should make a real effort to conserve energy.
6	0.10	I regularly pay attention to energy related issues because they affect me directly, not just our country.
7	0.15	I have sought ways to reduce my energy use in order to do what I can to protect the environment.
8	0.05	I monitor my home's energy use by reviewing my energy bill on a monthly basis.
9	0.05	Customers who use too much energy should pay higher rates as an incentive to conserve more.
10	0.15	I would be willing to pay a little more on my monthly electricity bill for "green" energy that comes from renewable sources.

Table A2: Farm-Rural and Residential Household Fixed Effects Demand Models

Model	**Farm-Rural**		**Residential**		**Model**	**Farm-Rural**		**Residential**	
Estimator	**FE**		**FE**		**Estimator**	**FE**		**FE**	
N	**371**		**230**		**N**	**371**		**230**	
T	**2178**		**2178**		**T**	**2178**		**2178**	
R-square	**0.864**		**0.480**		**R-square**	**0.864**		**0.480**	
Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|
Opt-Out_hr13	−0.425	0.014	−1.022	0.000	Opt-Out_hr13_Event	−0.712	0.242	−1.757	0.000
Opt-Out_hr14	−0.603	0.000	−1.214	0.000	Opt-Out_hr14_Event	−0.754	0.169	−0.928	0.025
Opt-Out_hr15	−0.353	0.037	−1.038	0.000	Opt-Out_hr15_Event	−0.367	0.469	−0.852	0.026
Opt-Out_hr16	−0.327	0.055	−1.002	0.000	Opt-Out_hr16_Event	0.232	0.639	−0.470	0.208
Opt-Out_hr17	−0.155	0.367	−0.927	0.000	Opt-Out_hr17_Event	−0.549	0.281	−0.851	0.026
Opt-Out_hr18	0.276	0.158	−0.561	0.000	Opt-Out_hr18_Event	−0.640	0.208	−0.604	0.114
Opt-Out_hr19	1.138	0.000	0.187	0.328	Opt-Out_hr19_Event	−1.077	0.035	−0.456	0.235
Opt-Out_hr20	0.059	0.840	−0.130	0.556	Opt-Out_hr20_Event	0.279	0.577	0.304	0.419
Opt-Out_hr21	−0.338	0.269	−0.343	0.136	Opt-Out_hr21_Event	1.883	0.001	1.060	0.013
Opt-Out_hr22	0.312	0.288	−0.276	0.211	Opt-Out_hr22_Event	1.624	0.004	0.603	0.149
Opt-In_hr13	−0.675	0.051	−1.144	0.000	Opt-In_hr13_Event	−2.836	0.020	−2.331	0.003
Opt-In_hr14	−1.176	0.001	−1.179	0.000	Opt-In_hr14_Event	−1.461	0.183	−1.260	0.076
Opt-In_hr15	−1.306	0.000	−1.180	0.000	Opt-In_hr15_Event	−0.580	0.569	−0.281	0.668
Opt-In_hr16	−0.877	0.010	−0.700	0.001	Opt-In_hr16_Event	−1.642	0.098	0.302	0.638
Opt-In_hr17	−0.814	0.018	−0.361	0.103	Opt-In_hr17_Event	−0.861	0.398	−0.372	0.571
Opt-In_hr18	−0.263	0.501	−0.066	0.794	Opt-In_hr18_Event	−0.863	0.397	−0.712	0.278
Opt-In_hr19	0.485	0.341	0.697	0.033	Opt-In_hr19_Event	−1.697	0.097	−1.158	0.078
Opt-In_hr20	−0.311	0.597	−0.282	0.455	Opt-In_hr20_Event	−0.681	0.496	0.947	0.142
Opt-In_hr21	−0.648	0.289	−0.168	0.669	Opt-In_hr21_Event	3.146	0.006	1.500	0.041
Opt-In_hr22	−0.258	0.661	−0.935	0.013	Opt-In_hr22_Event	1.964	0.078	1.326	0.065
IHD_hr13	−0.962	0.000	−0.951	0.000	IHD_hr13_Event	−0.774	0.215	−1.821	0.000
IHD_hr14	−1.109	0.000	−1.277	0.000	IHD_hr14_Event	−0.386	0.493	−0.731	0.079
IHD_hr15	−0.967	0.000	−1.207	0.000	IHD_hr15_Event	−0.091	0.861	−0.060	0.875
IHD_hr16	−0.793	0.000	−0.888	0.000	IHD_hr16_Event	−0.459	0.367	−0.339	0.367
IHD_hr17	−0.777	0.000	−0.792	0.000	IHD_hr17_Event	−0.512	0.328	−0.701	0.069
IHD_hr18	−0.185	0.357	−0.453	0.002	IHD_hr18_Event	−0.206	0.694	−0.646	0.094
IHD_hr19	0.578	0.027	0.243	0.209	IHD_hr19_Event	−1.196	0.023	−0.978	0.012
IHD_hr20	0.205	0.498	−0.266	0.233	IHD_hr20_Event	0.069	0.893	0.253	0.504
IHD_hr21	−0.331	0.292	−0.299	0.197	IHD_hr21_Event	0.877	0.134	1.209	0.005
IHD_hr22	0.332	0.271	−0.216	0.333	IHD_hr22_Event	0.520	0.363	1.096	0.009

(continued)

Table A2: **Farm-Rural and Residential Household Fixed Effects Demand Models** *(continued)*

Model	Farm-Rural		Residential		Model	Farm-Rural		Residential	
Estimator	FE		FE		Estimator	FE		FE	
N	371		230		N	371		230	
T	2178		2178		T	2178		2178	
R-square	0.864		0.480		R-square	0.864		0.480	
Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|
Opt-Out_hr13_CDH	0.063	0.000	0.047	0.000	Opt-Out_hr13_CDH_Event	0.011	0.251	0.013	0.085
Opt-Out_hr14_CDH	0.065	0.000	0.047	0.000	Opt-Out_hr14_CDH_Event	0.021	0.032	0.018	0.017
Opt-Out_hr15_CDH	0.071	0.000	0.057	0.000	Opt-Out_hr15_CDH_Event	0.021	0.046	0.017	0.038
Opt-Out_hr16_CDH	0.071	0.000	0.056	0.000	Opt-Out_hr16_CDH_Event	0.019	0.111	0.022	0.013
Opt-Out_hr17_CDH	0.070	0.000	0.056	0.000	Opt-Out_hr17_CDH_Event	0.018	0.184	0.022	0.026
Opt-Out_hr18_CDH	0.076	0.000	0.059	0.000	Opt-Out_hr18_CDH_Event	−0.002	0.877	−0.012	0.279
Opt-Out_hr19_CDH	0.086	0.000	0.066	0.000	Opt-Out_hr19_CDH_Event	0.002	0.900	−0.009	0.480
Opt-Out_hr20_CDH	0.059	0.000	0.056	0.000	Opt-Out_hr20_CDH_Event	−0.012	0.444	−0.021	0.087
Opt-Out_hr21_CDH	0.049	0.000	0.051	0.000	Opt-Out_hr21_CDH_Event	0.005	0.764	−0.008	0.480
Opt-Out_hr22_CDH	0.061	0.000	0.053	0.000	Opt-Out_hr22_CDH_Event	−0.008	0.568	−0.032	0.003
Opt-In_hr13_CDH	0.037	0.000	0.052	0.000	Opt-In_hr13_CDH_Event	0.017	0.390	0.024	0.053
Opt-In_hr14_CDH	0.034	0.000	0.060	0.000	Opt-In_hr14_CDH_Event	0.034	0.087	0.012	0.330
Opt-In_hr15_CDH	0.040	0.000	0.065	0.000	Opt-In_hr15_CDH_Event	0.030	0.160	−0.003	0.856
Opt-In_hr16_CDH	0.045	0.000	0.076	0.000	Opt-In_hr16_CDH_Event	0.017	0.469	−0.016	0.291
Opt-In_hr17_CDH	0.041	0.000	0.080	0.000	Opt-In_hr17_CDH_Event	0.000	0.988	−0.005	0.788
Opt-In_hr18_CDH	0.052	0.000	0.079	0.000	Opt-In_hr18_CDH_Event	−0.034	0.242	−0.014	0.442
Opt-In_hr19_CDH	0.065	0.000	0.099	0.000	Opt-In_hr19_CDH_Event	−0.044	0.218	−0.045	0.047
Opt-In_hr20_CDH	0.053	0.000	0.067	0.000	Opt-In_hr20_CDH_Event	−0.027	0.396	−0.053	0.010
Opt-In_hr21_CDH	0.041	0.004	0.075	0.000	Opt-In_hr21_CDH_Event	0.070	0.022	−0.038	0.051
Opt-In_hr22_CDH	0.041	0.004	0.063	0.000	Opt-In_hr22_CDH_Event	0.017	0.552	−0.055	0.003
IHD_hr13_CDH	0.050	0.000	0.051	0.000	IHD_hr13_CDH_Event	−0.001	0.925	0.013	0.076
IHD_hr14_CDH	0.051	0.000	0.053	0.000	IHD_hr14_CDH_Event	0.018	0.079	0.007	0.338
IHD_hr15_CDH	0.057	0.000	0.060	0.000	IHD_hr15_CDH_Event	0.010	0.344	0.008	0.351
IHD_hr16_CDH	0.061	0.000	0.063	0.000	IHD_hr16_CDH_Event	0.014	0.242	0.011	0.212
IHD_hr17_CDH	0.063	0.000	0.064	0.000	IHD_hr17_CDH_Event	0.012	0.378	0.021	0.039
IHD_hr18_CDH	0.067	0.000	0.066	0.000	IHD_hr18_CDH_Event	−0.012	0.429	0.003	0.756
IHD_hr19_CDH	0.080	0.000	0.077	0.000	IHD_hr19_CDH_Event	−0.007	0.709	−0.014	0.301
IHD_hr20_CDH	0.066	0.000	0.058	0.000	IHD_hr20_CDH_Event	−0.025	0.137	−0.011	0.380
IHD_hr21_CDH	0.045	0.000	0.053	0.000	IHD_hr21_CDH_Event	−0.003	0.871	−0.007	0.573
IHD_hr22_CDH	0.062	0.000	0.054	0.000	IHD_hr22_CDH_Event	−0.025	0.084	−0.012	0.260

(continued)

Table A2: Farm-Rural and Residential Household Fixed Effects Demand Models *(continued)*

Model	Farm-Rural		Residential		Model	Farm-Rural		Residential	
Estimator	**FE**		**FE**		**Estimator**	**FE**		**FE**	
N	**371**		**230**		**N**	**371**		**230**	
T	**2178**		**2178**		**T**	**2178**		**2178**	
R-square	**0.864**		**0.480**		**R-square**	**0.864**		**0.480**	
Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|
Opt-Out_hr13_DP	0.014	0.000	0.017	0.000	Opt-Out_hr13_DP_Event	0.009	0.274	0.022	0.000
Opt-Out_hr14_DP	0.016	0.000	0.021	0.000	Opt-Out_hr14_DP_Event	0.005	0.437	0.007	0.188
Opt-Out_hr15_DP	0.013	0.000	0.017	0.000	Opt-Out_hr15_DP_Event	−0.002	0.715	0.004	0.336
Opt-Out_hr16_DP	0.015	0.000	0.019	0.000	Opt-Out_hr16_DP_Event	−0.011	0.077	−0.005	0.311
Opt-Out_hr17_DP	0.015	0.000	0.020	0.000	Opt-Out_hr17_DP_Event	−0.001	0.858	−0.001	0.818
Opt-Out_hr18_DP	0.011	0.002	0.018	0.000	Opt-Out_hr18_DP_Event	0.006	0.377	0.006	0.252
Opt-Out_hr19_DP	−0.002	0.622	0.007	0.033	Opt-Out_hr19_DP_Event	0.012	0.116	0.004	0.510
Opt-Out_hr20_DP	0.017	0.002	0.015	0.000	Opt-Out_hr20_DP_Event	0.000	0.977	−0.001	0.882
Opt-Out_hr21_DP	0.023	0.000	0.019	0.000	Opt-Out_hr21_DP_Event	−0.023	0.022	−0.010	0.195
Opt-Out_hr22_DP	0.012	0.020	0.017	0.000	Opt-Out_hr22_DP_Event	−0.016	0.105	0.002	0.828
Opt-In_hr13_DP	0.014	0.025	0.020	0.000	Opt-In_hr13_DP_Event	0.036	0.020	0.024	0.019
Opt-In_hr14_DP	0.022	0.000	0.020	0.000	Opt-In_hr14_DP_Event	0.011	0.393	0.011	0.188
Opt-In_hr15_DP	0.024	0.000	0.020	0.000	Opt-In_hr15_DP_Event	0.000	0.979	0.003	0.691
Opt-In_hr16_DP	0.017	0.005	0.015	0.000	Opt-In_hr16_DP_Event	0.011	0.370	−0.008	0.281
Opt-In_hr17_DP	0.024	0.000	0.014	0.001	Opt-In_hr17_DP_Event	−0.002	0.890	−0.009	0.273
Opt-In_hr18_DP	0.018	0.012	0.014	0.002	Opt-In_hr18_DP_Event	0.004	0.774	−0.002	0.793
Opt-In_hr19_DP	0.005	0.598	0.000	0.968	Opt-In_hr19_DP_Event	0.015	0.333	0.012	0.218
Opt-In_hr20_DP	0.019	0.080	0.022	0.001	Opt-In_hr20_DP_Event	0.005	0.751	−0.007	0.544
Opt-In_hr21_DP	0.026	0.015	0.019	0.006	Opt-In_hr21_DP_Event	−0.055	0.006	−0.007	0.608
Opt-In_hr22_DP	0.021	0.042	0.031	0.000	Opt-In_hr22_DP_Event	−0.026	0.170	−0.003	0.840
IHD_hr13_DP	0.020	0.000	0.017	0.000	IHD_hr13_DP_Event	0.013	0.111	0.020	0.001
IHD_hr14_DP	0.023	0.000	0.022	0.000	IHD_hr14_DP_Event	0.001	0.919	0.006	0.222
IHD_hr15_DP	0.020	0.000	0.021	0.000	IHD_hr15_DP_Event	−0.002	0.713	−0.004	0.440
IHD_hr16_DP	0.018	0.000	0.017	0.000	IHD_hr16_DP_Event	0.001	0.884	−0.002	0.645
IHD_hr17_DP	0.020	0.000	0.019	0.000	IHD_hr17_DP_Event	0.001	0.894	−0.002	0.736
IHD_hr18_DP	0.015	0.000	0.018	0.000	IHD_hr18_DP_Event	0.005	0.466	0.005	0.339
IHD_hr19_DP	0.002	0.618	0.008	0.029	IHD_hr19_DP_Event	0.019	0.015	0.015	0.011
IHD_hr20_DP	0.010	0.078	0.019	0.000	IHD_hr20_DP_Event	0.007	0.399	−0.001	0.833
IHD_hr21_DP	0.022	0.000	0.022	0.000	IHD_hr21_DP_Event	−0.007	0.487	−0.014	0.055
IHD_hr22_DP	0.011	0.037	0.019	0.000	IHD_hr22_DP_Event	0.002	0.815	−0.011	0.135

Table A3: Farm-Rural and Residential Household Fixed Effects Household Characteristics Demand Models

Test Group	IFR		VFR		TFR		IRS		VRS		TRS	
Estimator	FE		FE		FE		FE		FE		FE	
N	95		42		55		32		21		25	
T	2178		2178		2178		2178		2178		2178	
R-square	0.756		0.497		0.825		0.405		0.606		0.372	
Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|
CDH	0.051	0.000	0.040	0.000	0.054	0.000	0.049	0.000	0.067	0.000	0.052	0.000
DP	0.011	0.000	0.019	0.000	0.013	0.000	0.015	0.000	0.014	0.000	0.008	0.000
hr13	0.300	0.030	0.263	0.076	1.277	0.000	−0.603	0.000	−0.012	0.955	−1.333	0.000
hr14	0.327	0.018	0.297	0.045	1.399	0.000	−0.562	0.000	−0.017	0.937	−0.930	0.000
hr15	0.465	0.001	0.174	0.243	0.985	0.000	−0.418	0.002	−0.191	0.364	−0.651	0.013
hr16	0.702	0.000	0.421	0.005	1.041	0.000	−0.392	0.004	0.053	0.802	−0.315	0.228
hr17	1.180	0.000	1.178	0.000	0.780	0.000	−0.106	0.439	0.308	0.143	−0.152	0.561
hr18	1.472	0.000	0.931	0.000	0.960	0.000	0.636	0.000	0.750	0.000	0.342	0.192
hr19	1.275	0.000	0.804	0.000	0.929	0.000	0.981	0.000	1.119	0.000	0.192	0.465
hr20	1.018	0.000	0.435	0.003	0.840	0.000	1.215	0.000	1.018	0.000	0.208	0.426
hr21	1.070	0.000	0.424	0.004	0.859	0.000	1.010	0.000	0.853	0.000	−0.045	0.864
hr22	0.923	0.000	0.472	0.002	0.838	0.000	0.761	0.000	0.920	0.000	−0.130	0.619
CAC_hr13	0.431	0.000	0.155	0.110	0.418	0.000	0.853	0.000	0.473	0.001	0.428	0.035
CAC_hr14	0.480	0.000	0.133	0.168	0.383	0.000	0.904	0.000	0.445	0.001	0.288	0.155
CAC_hr15	0.606	0.000	0.224	0.021	0.423	0.000	0.896	0.000	0.629	0.000	0.451	0.026
CAC_hr16	0.634	0.000	0.157	0.104	0.323	0.002	1.014	0.000	0.831	0.000	0.469	0.021
CAC_hr17	0.701	0.000	−0.750	0.000	0.431	0.000	1.080	0.000	1.223	0.000	0.634	0.002
CAC_hr18	0.783	0.000	−0.693	0.000	0.553	0.000	1.059	0.000	1.343	0.000	0.595	0.003
CAC_hr19	0.686	0.000	−0.049	0.611	0.570	0.000	0.853	0.000	1.165	0.000	0.656	0.001
CAC_hr20	0.483	0.000	0.510	0.000	0.496	0.000	0.706	0.000	1.203	0.000	0.586	0.004
CAC_hr21	0.416	0.000	0.636	0.000	0.622	0.000	0.700	0.000	1.044	0.000	0.673	0.001
CAC_hr22	0.429	0.000	0.700	0.000	0.652	0.000	0.533	0.000	0.936	0.000	0.658	0.001
pctgn_hr13	−0.062	0.720	−0.123	0.504	−1.880	0.000	0.263	0.055	−0.050	0.810	1.618	0.000
pctgn_hr14	−0.122	0.484	−0.220	0.233	−1.977	0.000	0.206	0.132	0.072	0.731	1.355	0.000
pctgn_hr15	−0.294	0.091	−0.069	0.709	−1.339	0.000	0.074	0.592	0.176	0.402	0.840	0.000
pctgn_hr16	−0.506	0.004	−0.207	0.262	−1.176	0.000	0.058	0.674	−0.013	0.952	0.519	0.020
pctgn_hr17	−0.970	0.000	0.279	0.131	−0.720	0.000	−0.108	0.429	−0.298	0.156	0.400	0.073
pctgn_hr18	−1.115	0.000	1.076	0.000	−0.736	0.000	−0.812	0.000	−0.833	0.000	0.298	0.183
pctgn_hr19	−0.638	0.000	0.565	0.002	−0.615	0.000	−0.946	0.000	−1.184	0.000	0.580	0.009
pctgn_hr20	−0.236	0.175	0.384	0.038	−0.532	0.002	−1.111	0.000	−0.962	0.000	0.773	0.001
pctgn_hr21	−0.247	0.156	0.362	0.051	−0.656	0.000	−0.801	0.000	−0.654	0.002	1.215	0.000

(continued)

Table A3: Farm-Rural and Residential Household Fixed Effects Household Characteristics Demand Models *(continued)*

Test Group	**IFR**		**VFR**		**TFR**		**IRS**		**VRS**		**TRS**	
Estimator	**FE**		**FE**		**FE**		**FE**		**FE**		**FE**	
N	**95**		**42**		**55**		**32**		**21**		**25**	
T	**2178**		**2178**		**2178**		**2178**		**2178**		**2178**	
R-square	**0.756**		**0.497**		**0.825**		**0.405**		**0.606**		**0.372**	
Variable	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|	Parameter Estimates	Pr>|t|
pctgn_hr22	0.006	0.974	0.332	0.073	−0.506	0.003	−0.300	0.029	−0.733	0.001	1.168	0.000
event_hr13	0.112	0.686	−0.220	0.460	0.320	0.276	−0.911	0.001	−0.747	0.079	0.527	0.316
event_hr14	−0.203	0.465	−0.289	0.333	0.452	0.124	−0.673	0.015	−1.534	0.000	0.692	0.188
event_hr15	−0.254	0.360	−0.005	0.988	0.521	0.076	−0.539	0.051	−0.939	0.027	1.970	0.000
event_hr16	0.298	0.283	−0.442	0.138	0.164	0.576	−0.547	0.047	−1.314	0.002	2.153	0.000
event_hr17	0.196	0.480	−0.849	0.004	0.302	0.304	−0.167	0.544	−0.495	0.245	2.212	0.000
event_hr18	0.234	0.400	−0.777	0.009	0.458	0.120	−0.292	0.290	−0.677	0.112	1.787	0.001
event_hr19	0.472	0.089	−0.722	0.015	0.658	0.025	−0.302	0.274	−1.003	0.019	2.131	0.000
event_hr20	0.329	0.235	−0.201	0.501	0.870	0.003	−0.434	0.116	−0.259	0.543	1.845	0.001
event_hr21	0.225	0.418	−0.352	0.238	1.082	0.000	0.096	0.728	0.791	0.063	2.016	0.000
event_hr22	0.406	0.144	−0.305	0.306	1.216	0.000	−0.406	0.141	1.127	0.008	1.897	0.000
CAC_event_hr13	0.567	0.001	0.245	0.210	0.290	0.175	0.989	0.000	0.050	0.858	−0.735	0.072
CAC_event_hr14	0.508	0.002	0.441	0.024	0.332	0.121	0.773	0.000	0.295	0.288	−0.391	0.338
CAC_event_hr15	0.482	0.004	0.405	0.038	0.330	0.123	0.771	0.000	0.115	0.679	−1.099	0.007
CAC_event_hr16	0.328	0.047	0.104	0.594	0.475	0.027	0.495	0.013	−0.305	0.272	−0.930	0.023
CAC_event_hr17	0.210	0.204	−0.253	0.196	0.063	0.770	0.085	0.671	−1.044	0.000	−0.796	0.051
CAC_event_hr18	0.147	0.372	−0.105	0.592	−0.087	0.685	0.012	0.954	−1.014	0.000	−0.340	0.406
CAC_event_hr19	0.350	0.034	−0.003	0.989	−0.001	0.998	0.116	0.563	−0.614	0.027	−0.432	0.291
CAC_event_hr20	0.452	0.006	−0.251	0.199	0.025	0.906	0.403	0.044	0.042	0.878	−0.268	0.511
CAC_event_hr21	0.389	0.019	0.448	0.022	0.122	0.569	0.529	0.008	1.146	0.000	−0.546	0.182
CAC_event_hr22	0.296	0.074	0.354	0.071	0.116	0.587	0.874	0.000	1.164	0.000	−0.878	0.032
pctgn_event_hr13	−0.521	0.137	0.099	0.789	−0.895	0.009	0.606	0.028	0.722	0.087	0.215	0.632
pctgn_event_hr14	0.130	0.711	0.193	0.605	−0.952	0.005	0.180	0.514	1.579	0.000	−0.343	0.444
pctgn_event_hr15	0.123	0.725	−0.046	0.901	−1.092	0.001	−0.023	0.934	1.046	0.013	−1.029	0.022
pctgn_event_hr16	−0.632	0.071	−0.063	0.865	−0.831	0.015	0.020	0.941	1.160	0.006	−1.558	0.001
pctgn_event_hr17	−0.732	0.036	0.153	0.682	−0.888	0.010	−0.444	0.108	0.254	0.548	−2.032	0.000
pctgn_event_hr18	−0.801	0.022	−0.494	0.185	−0.906	0.008	−0.197	0.477	0.298	0.480	−1.937	0.000
pctgn_event_hr19	−1.306	0.000	−0.927	0.013	−1.029	0.003	−0.223	0.419	0.437	0.302	−2.438	0.000
pctgn_event_hr20	−0.954	0.006	−0.394	0.290	−1.163	0.001	0.108	0.695	−0.166	0.695	−1.935	0.000
pctgn_event_hr21	−0.254	0.468	0.706	0.058	−1.229	0.000	−0.163	0.555	−1.203	0.005	−1.561	0.001
pctgn_event_hr22	−0.280	0.424	0.678	0.069	−1.363	0.000	0.106	0.700	−1.714	0.000	−0.752	0.094