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EXHIBIT 6:
Household Response to Dynamic Pricing of Electricity:
A Survey of Experimental Evidence
by Ahmad Faruqui and Sanem Sergici

HOUSEHOLD RESPONSE TO DYNAMIC PRICING OF ELECTRICITY—A SURVEY OF THE EMPIRICAL EVIDENCE

Ahmad Faruqui and Sanem Sergici[1]

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HOUSEHOLD RESPONSE TO DYNAMIC PRICING OF ELECTRICITY—A SURVEY OF THE EMPIRICAL EVIDENCE

Since the energy crisis of 2000-2001 in the western United States, much attention has been given to boosting demand response in electricity markets. One of the best ways to let that happen is to pass through wholesale energy costs to retail customers. This can be accomplished by letting retail prices vary dynamically, either entirely or partly. For the overwhelming majority of customers, that requires a changeout of the metering infrastructure, which may cost as much as $40 billion for the US as a whole. While a good portion of this investment can be covered by savings in distribution system costs, about 40 percent may remain uncovered. This investment gap could be covered by reductions in power generation costs that could be brought about through demand response. Thus, state regulators in many states are investigating whether customers will respond to the higher prices by lowering demand and if so, by how much.

To help inform this assessment, we survey the evidence from the 15 most recent pilots, experiments and full-scale implementations of dynamic pricing of electricity. We find conclusive evidence that households (residential customers) respond to higher prices by lowering usage. The magnitude of price response depends on several factors, such as the magnitude of the price increase, the presence of central air conditioning and the availability of enabling technologies such as two-way programmable communicating thermostats and always-on gateway systems that allow multiple end-uses to be controlled remotely. They also vary with the design of the studies, the tools used to analyze the data and the geography of the assessment. Across the range of experiments studied, time-of-use rates induce a drop in peak demand that ranges between three to six percent and critical-peak pricing tariffs induce a drop in peak demand that ranges between 13 to 20 percent. When accompanied with enabling technologies, the latter set of tariffs lead to a drop in peak demand in the 27 to 44 percent range.

1. INTRODUCTION

Electricity cannot be stored economically in large quantities, and has to be consumed instantly on demand. The load duration curve for most utility systems is very peaky, with some 8 to 10 percent of annual peak load concentrated in the top one percent of the hours of the year. These two factors, taken in conjunction with the variation in marginal energy and capacity costs that characterizes different generation technologies, mean that the optimal way for pricing electricity would be for regulators to institute time-varying rates for generation service provided either by vertically-integrated utilities in non-restructured states or by distribution-only utilities that provide standard offer service in restructured states.[2] Nevertheless, for the past century,

[2] For a survey, see Crew, Fernando and Kleindorfer (1995). A case for dynamic as opposed to static time-varying rates was provided by Vickrey (1971). Chao (1983) introduced uncertainty into the analysis. Littlechild (2003) made a case for passing through wholesale costs to retail customers. Borenstein (2005) compared the efficiency gains of dynamic and static time-varying rates.

electricity pricing has violated this optimality condition and been based on average cost. This has had the unfortunate effect of encouraging excessive consumption of electricity during the expensive peak-period hours and discouraging consumption during the inexpensive off-peak period hours. Over time, as the penetration of central air conditioning systems has deepened in most parts of the country, load factors have deteriorated and the peak loads have become more pronounced. To eliminate the deadweight loss associated with average-cost pricing, prices during the off-peak period should be set equal to the marginal cost of energy and prices during the peak period should be set equal to the marginal cost of energy and capacity. There is widespread consensus in the economics literature that such a shift in the pricing paradigm would increase both consumer surplus and producer surplus and raise societal welfare by lowering the average cost of electricity. Such a change would also pass most the "standard practice" tests that are used by state commissions to evaluate demand-side programs.[3]

So why has practice lagged theory, creating one of the longest-lasting paradoxes in the field of public utility regulation? There are several reasons, with the foremost being the cost of installing the advanced metering infrastructure (AMI) that would allow dynamic pricing to be implemented. This debate usually centers around two important questions. First, whether or not customers would respond to higher prices by reducing demand.[4] And second, whether it would make economic sense to equip millions of residential and small commercial and industrial customers with the AMI that would be necessary to transmit such dynamic price signals to them.[5]

California Public Utilities Commission (CPUC) initiated a proceeding on advanced metering, demand response and dynamic pricing to answer these questions for its own jurisdiction.[6] As part of the proceeding, the state carried out one of the most comprehensive experiments with dynamic pricing. It showed conclusively that residential customers responded to prices that were

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3 Earle and Faruqui (2006).

4 This question was answered at least temporarily in San Diego where wholesale prices were allowed to flow through to retail customers in the summer of 2000. When prices doubled, customers lowered their usage by 13 percent. See Reiss and White (2008).

5 The question of whether meter changeout is cost-effective does not arise for large commercial and industrial customers since such a changeout is prima facie cost-effective. In addition, there is substantial evidence on the price responsiveness of such customers. See, for example, Taylor, Schwarz and Cochell (2005) and the case studies in Faruqui and Eakin (2000) and (2002).

6 CPUC R. 02-06-001. http://docs.cpuc.ca.gov/published/proceedings/R0206001.htm.

five times higher than the standard tariff during the top 75 hours of the year by lowering usage by 13 percent.[7] The three investor-owned utilities in the state relied on the results from the experiment to develop their AMI business cases. They showed that while AMI yielded many operational benefits to the distribution system, such benefits only covered about sixty percent of the total investment. The remaining forty percent had to be covered through demand response. The CPUC has approved all three business cases.

Similar discussions are taking place in many jurisdictions throughout North America, spurred in part by two federal laws.[8] Both restructured and traditionally regulated states are simultaneously engaged in this re-examination of metering and demand response issues. A survey of state regulatory activity carried out in August 2008 found that 38 commissions had initiated regulatory consideration of smart meters and demand response in response to federal legislation and 32 had completed their consideration.[9] The momentum toward dynamic pricing and demand response has also extended to wholesale markets. Many regional transmission organizations and independent system operators around the US including those in California, the Midwest, New England, New York and PJM are giving serious consideration to introducing demand response in wholesale markets. A recent analysis showed that even a five percent reduction in US demand during the top one percent of the hours of the years would yield a present value of $35 billion in benefits.[10]

To effectuate demand response, some type of dynamic pricing will have to be instituted in retail markets.[11] The central question in all of these assessments is: *Will customers respond to higher prices by lowering peak demand and if so, by how much?* The answer will help state regulators determine whether or not to proceed with authorizing the deployment of AMI in their jurisdictions. Is it worthwhile to pursue AMI? The answer is a conditional yes. Two things

7 Faruqui and George (2005), Herter (2007), and Herter, McAuliffe and Rosenfeld (2007).

8 The Energy Policy Act of 2005 and The Energy Independence and Security Act of 2007 ask state commissions to consider the deployment of smart meters and demand response. The latter act also asks the Federal Energy Regulatory Commission to carry out a state-by-state assessment of the potential for demand response.

9 US Demand Response Coordinating Committee, (2008).

10 Faruqui, Hledik, Newell and Pfeiffenberger (2007). With updated assumptions about the cost of peaking capacity, the benefit estimate might be closer to $66 billion.

11 Wellinghoff and Morenoff (2007).

have to occur to make this a sound decision. First, AMI should be accompanied by dynamic pricing to get the most value out of the investment. This represents a major change in the pricing paradigm and will be actively debated by commissions in every state before a consensus is arrived at. Second, customer response to dynamic pricing has to create savings in avoided capacity and energy costs to overcome the net investment in AMI (i.e., that amount which is not offset by savings in distribution system costs). The second condition is largely an empirical issue and provides the impetus for this paper.

In Section 2, we provide an overview of 15 recent empirical assessments of dynamic pricing. Several were conducted as scientifically designed experiments with balanced control and treatment groups, a few were designed with treatment groups that were not randomly chosen and some are full-scale deployments with no experimental controls. We tabulate the design characteristics of these 15 assessments and review in detail the design of each individual assessment and present its results. In this section we compare the results across experiments and also illustrate the likely effect of dynamic pricing on customer peak loads by relying on the results of one of the most widely-cited pricing experiments. In Section 3, we conclude our paper.

2. THE FIFTEEN EXPERIMENTS

In the late 1970s and early 1980s, the first wave of electricity pricing experiments was carried out under the auspices of the US Federal Energy Administration. Those experiments were focused on measuring customer response to simple (static) time-of-day and seasonal rates.[12] The data from the top five experiments, located in California, Connecticut, North Carolina and Wisconsin, were analyzed in a major study carried out for the Electric Power Research Institute (EPRI).[13]

EPRI study used the constant elasticity of substitution (CES) model to analyze the customer response. This model merits some discussion since it has also been used in several subsequent studies. Data in electricity pricing studies that involve individual customers, whether experimental or otherwise, is limited to repeated observations of electricity consumption and

[12] Faruqui and Malko (1983).
[13] Caves, Christensen, and Herriges (1984).

prices by period. Thus, if the analyst wishes to estimate demand functions that are consistent with the theory of utility maximization, he or she is forced to assume a two-stage budgeting process on the consumer's part. Often, this means invoking the assumption of homothetic separability in consumer preferences which posits inter alia that the ratio of peak to off-peak consumption does not depend on the amount being spent on electricity. The CES model allows the elasticity of substitution to take on any value and it has been found to be well-suited to TOU pricing studies involving electricity since there is strong prior evidence suggesting that these elasticities are going to be small. Appendix provides a formal representation of the CES model.

The results of the EPRI study were conclusive: customers responded to higher prices during the peak period by reducing peak period usage and/or shifting it to less expensive off-peak periods. The results were consistent around the country once weather conditions and appliance holdings were held constant. Customer response was higher in warmer climates and for customers with all electric homes.

However, despite the conclusive findings from the EPRI study, time-varying rates were not widely accepted across the country.[14] Most customers did not even know such rates existed for a long time. Almost two decades later, California's energy crisis rekindled interest in time-varying rates and set off the second wave of electricity pricing experiments. However, there were noticeable differences between the rate designs tested in the first and second waves of the pricing experiments. In the second wave, a variety of academics, researchers and consultants called for the institution of rates that would be dynamically dispatchable during critical-price periods. These occur typically during the top one percent of the hours of the year where, as noted earlier, somewhere between 9-17 percent of the annual peak demand is concentrated. It is very expensive to serve power during these critical periods and even a modest reduction in demand can be very cost-effective.

In this section, we profile 15 experiments from the second wave by presenting their salient design features, estimated impacts and, wherever they were provided, the price and substitution

14 There were three reasons for this. First, the high cost of time-of-use metering. Second, the peak periods in the TOU rate designs were too broad to garner customer acceptance. And third, for reasons that are not entirely clear, the utilities failed to market the programs effectively.

elasticities. It is important to note that the pricing pilots experiments reviewed in this study are largely heterogeneous in terms of their designs and the quality of information varies considerably across the studies which sometimes get in the way of providing a consistent perspective. In this paper, we don't attempt to control for differences in the design of the experiments. However, we describe each experiment in sufficient detail so that readers can place each experiment in perspective.

The study designs are presented in Table 1. Most of them are based on panel data, involving repeated measurements on a cross-section of customers. Some of the customers are placed on the dynamic pricing rate (or rates) and fall into the treatment group. Others stay on existing rates and fall into the control group. To be a true experiment, the treatment and control groups should be randomly chosen. Otherwise, the design becomes a quasi experiment.[15] The better designs feature measurement during the pre-treatment period which allows any potential self-selection bias in the treatment group to be detected. This also allows for the application of the "difference-in- differences" estimator, obtained by subtracting (any) pre-existing difference in the usage of the control group between treatment and pre-treatment periods from that of the treatment group between the treatment and pre-treatment periods. Finally, the superior designs feature multiple price points, allowing for the estimation of demand models and price and substitution elasticities which can be used to predict not only the impact of the specific rates tested in the study but also other rates. The simpler designs had a single time-varying rate and only allowed a comparison of means to be carried out using either analysis of variance (ANOVA) or covariance (ANCOVA). The results in such cases are limited to the time-varying rates tested in the study and cannot be used to assess alternative values of peak and off-peak prices.

15 Shadish, Cook and Campbell (2002).

Table 1- Overview of the Studies

No	State/ Province	Experiment	Utility	Year	Involved a Control Group?	Number of Customers	Number of Rates Tested	Link to Figure 1
1	California	Anaheim Critical Peak Pricing Experiment	Anaheim Public Utilities (APU)	2005	Yes	52 control, 71 treatment	1	Anaheim
2	California	California Automated Demand Response System Pilot (ADRS)	Pacific Gas & Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E)	2004-2005	Yes	In 2004: 104 control, 122 treatment In 2005: 101 control, 98 treatment	1	ADRS-04, ADRS-05
3	California	California Statewide Pricing Pilot (SPP)	Pacific Gas & Electric (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric (SDG&E)	2003-2004	Yes	2,500 customers	3	SPP, SPP-A, SPP-C
4	Colorado	Xcel Experimental Residential Price Response Pilot Program	Xcel Energy	2006-2007	Yes	1350 control, 2349 treatment	3	XCEL-TOU, XCEL-CPP, XCEL-CTOU
5	Florida	The Gulf Power Select Program	Gulf Power	2000-2001	Yes	2300 customers participating in the RSVP program	2	GulfPower-1, GulfPower-2
6	France	Electricite de France (EDF) Tempo Program	Electricite de France (EDF)	Since 1996	-	400,000 customers	1	-
7	Idaho	Idaho Residential Pilot Program	Idaho Power Company	2005-2006	Yes	TOD Program- 420 control, 85 treatment EW Program- 355 control, 68 treatment	2	Idaho
8	Illinois	The Community Energy Cooperative's Energy-Smart Pricing Plan (ESPP)	Commonwealth Edison	2003-2005	Yes	1,500 customers	2	ESPP
9	Missouri	AmerenUE Residential TOU Pilot Study	AmerenUE	2004-2005	Yes	TOU - 89 control, 88 treatment TOU/CPP- 89 control , 85 treatment TOU/CPP w/ Technology- 117 control, 77 treatment	2	Ameren-04, Ameren-05
10	New Jersey	GPU Pilot	GPU	1997	Yes	Not Available	2	GPU
11	New Jersey	Public Service Electric and Gas (PSE&G) Residential Pilot Program	Public Service Electric and Gas Company (PSE&G)	2006-2007	Yes	450 control, 836 treatment	1	PSE&G
12	New South Wales (Australia)	Energy Australia's Network Tariff Reform	Energy Australia	2005	Yes	TOU program: 50,000 customers SPS: 1300 treatment	Tested several dynamic tariffs	Australia
13	Ontario (Canada)	Ontario Energy Board Smart Price Pilot	Hydro Ottawa	2006-2007	Yes	125 control, 373 treatment	3	Ontario-1, Ontario-2
14	Washington	Puget Sound Energy (PSE)'s TOU Program	Puget Sound Energy	2001-2002	-	300,000 customers	1	PSE
15	Washington and Oregon	Olympic Peninsula Project	Bonneville Power Administration, Clallam County PUD, The City of Port Angeles, Portland General Electric, and PacifiCorp	2005	Yes	28 control, 84 treatment	3	Olympic P.

2.1. REVIEW OF THE FIFTEEN EXPERIMENTS

1. CALIFORNIA- ANAHEIM CRITICAL PEAK PRICING EXPERIMENT

The City of Anaheim Public Utilities (APU) conducted a residential dynamic pricing experiment between June 2005 and October 2005.[16] A total of 123 customers participated in the experiment: 52 in the control group and 71 in the treatment group. Despite its name, this experiment did not feature a critical peak pricing rate. Instead, it provided participants a rebate for each kWh reduction during critical hours. The magnitude of the peak time rebate (PTR) was $0.35 for each kWh reduction below the reference level peak-period consumption on non-CPP days (i.e., the baseline consumption). The rate design is presented in Table 2.

Table 2- Anaheim PTR Rate Design

Group	Charge	Applicable Period
Control	Standard increasing-block residential tariff: $0.0675/kWh if consumption <=240kWh per month $0.1102/kWh if consumption >240kWh per month	All hours
Treatment	Standard increasing-block residential tariff	All hours except except peak hours (12 a.m. - 6 p.m.) on CPP days
Treatment	$0.35 rebate for each kWh reduction relative to their typical peak consumption on non-CPP days.	Peak hours (12 a.m. - 6 p.m.) on CPP days

Statistical comparisons during the pre-treatment period between treatment and control group customers were not statistically significant indicating that the two groups were balanced and there was no self-selection bias. The data showed that the treatment group used 12 percent less electricity on average during the peak hours of the CPP days than the control group. Demand response by treatment customers was greater on higher temperature CPP days than on lower temperature CPP days.

16 Wolak (2006).

2. CALIFORNIA- AUTOMATED DEMAND RESPONSE SYSTEM PILOT[17]

California's Advanced Demand Response System (ADRS) pilot program was carried out on a subset of the customers who were included in the Statewide Pricing Pilot which is discussed in the next sub-section. All the ADRS participants were located in the upper portion of the Central Valley. The experiment was initiated in 2004 and extended through the end of 2005. ADRS operated under a critical peak pricing tariff that was identical to that in the SPP which was supported with a residential-scale, automated demand response technology. Participants of the pilot installed the GoodWatts system, an advanced home climate control system that allowed users to web-program their preferences for the control of home appliances. Under the CPP tariff, prices were higher during the peak period (2 p.m. to 7 p.m. on weekdays). All other hours, weekends, and holidays were subject to the base rate. When the "super peak events" were called, the peak price was three times higher than the regular peak price.

Program participants achieved substantial load reductions in both 2004 and 2005 compared to the control group. Load reductions on super peak event days were consistently about twice the size of load reductions during the peak periods on non-event days. In 2004, the peak reductions were as high as 51 percent on event days when participants faced a critical-peak pricing (CPP) rate and 32 percent on non-event days when participants faced a TOU rate. These impacts were respectively 43 percent and 27 percent in 2005, the second year of the program. Enabling technology emerged as the main driver of the load reductions especially on super peak event days and for the high consumption customers. Overall, load reductions of the ADRS participants were consistently larger than those of the other demand response program participants without the technology.

3. CALIFORNIA- STATEWIDE PRICING PILOT[18]

California's three investor-owned utilities, Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E), together with the two regulatory commissions conducted the Statewide Pricing Pilot (SPP) that ran from July 2003 to December 2004 to test the impact of several time-varying rates. The SPP included about 2,500 participants

[17] Rocky Mountain Institute (2006).

[18] Charles River Associates (2005), Faruqui and George (2005), Herter (2007) and Herter, McAuliffe and Rosenfeld (2007).

including residential and small-to-medium commercial and industrial (C&I) customers. SPP tested several rate structures. The first one was a TOU-only rate where the peak price was twice the value of the off-peak price. The second one was a CPP rate where the peak price during 15 "critical" days was roughly five times greater than the off-peak price; on non-critical days, a TOU rate applied. The SPP tested two variations of the CPP rates, CPP-F and CPP-V. The CPP-F rate had a fixed period of critical peak and day-ahead notification. CPP-F customers did not have an enabling technology. The CPP-V rate had a variable-length critical peak period and this was activated on a day-of basis. CPP-V customers were provided enabling technologies such as a two-way communicating smart thermostat.

CPP-F Impacts

The average price for customers on the standard rate was about $0.13 per kWh. Under the CPP-F rate, the average peak-period price on critical days was roughly $0.59 per kWh, the peak price on non-critical days was $0.22 per kWh, and the average off-peak price was $0.09 per kWh. CPP-F rate impacts are as follows:

- On critical days, statewide average reduction in peak-period energy use was estimated to be 13.1 percent. Impacts varied across the four climate zones which spanned a climate as diverse as that of San Francisco and Palm Springs ranged from a low of 7.6 percent to a high of 15.8 percent.
- The average peak-period impact on critical days during the inner summer months (July-September) was estimated to be 14.4 percent while the same impact was 8.1 percent during the outer summer months (May, June, and October).
- On normal weekdays, when just the TOU rate was in effect, the average impact was 4.7 percent, with a range across climate zones from 2.2 percent to 6.5 percent.
- No change in total energy use across the entire year was found based on the average SPP prices.
- The impact of different customer characteristics on energy use by rate period was also examined. Central air conditioning ownership and college education are the two customer characteristics that were associated with the largest reduction in energy use on critical days.

Table 3- Residential CPP-F Rate Impacts on Critical Days for Inner Summer Months (July, August, September)

Year			Start Value (kWh/hr)	Impact (kWh/hr)	Elasticity Estimate	T-stat	Impact (%)
2003	Rate Period	Peak	1.28	-0.163	-	-20.94	-12.71
		Off-peak	0.8	0.021	-	7.8	2.57
		Daily	0.9	-0.018	-	-6.88	-1.95
	Elasticity	Substitution	-	-	0.086	20.51	-
		Daily	-	-	-0.032	-6.8	-
2004	Rate Period	Peak	1.28	-0.178	-	-18.49	-13.93
		Off-peak	0.8	0.01	-	2.95	1.25
		Daily	0.9	-0.029	-	-8.7	-3.24
	Elasticity	Substitution	-	-	0.087	16.84	-
		Daily	-	-	-0.054	-8.55	-

TOU Impacts

The average price for customers on the standard rate was about $0.13 per kWh. Under the TOU rate, the average peak-period price was roughly $0.22 per kWh and the average off-peak price was $ 0.09 per kWh.

- The reduction in peak period energy use during the inner summer months of 2003 was estimated to be 5.9 percent. However, this impact completely disappeared in 2004.
- Due to small sample problems in the estimation of TOU impacts, normal weekday elasticities from the CPP-F treatment may serve as better predictors of the impact of TOU rates on energy demand than the TOU price elasticity estimates.

CPP-V Impacts

These customers were located in the San Diego metropolitan area. The average price for customers on the standard rate was about $0.14 per kWh. Under the CPP-V rate, the average peak-period price on critical days was roughly $0.65 per kWh and the average off-peak price was $0.10 per kWh. This rate schedule was tested on two different treatment groups. Track A customers were drawn from a population with energy use greater than 600 kWh per month. In this group, average income and central AC saturation was much higher than the general population. Track A customers were given a choice of installing an enabling technology and about two thirds of them opted for the enabling technology. The Track C group was formed from customers who previously volunteered for a smart thermostat pilot. All Track C customers had central AC and smart thermostats. Hence, two-thirds of Track A customers and all Track C customers had enabling technologies.

Table 4- Residential CPP-V Rate Impacts for Summer for All Customers

			Start Value (kWh/hr)	Impact (kWh/hr)	Elasticity Estimate	t-stat	Impact (%)
Track A	Rate Period	Peak	2.14	-0.3374	-	-10.89	-15.76
		Off-peak	1.33	0.0445	-	4.26	3.34
		Daily	1.46	-0.0187	-	-1.71	-1.28
		Weekend Daily	1.3	0.0173	-	2.72	1.33
	Elasticity	Substitution	-	-	0.111	11.76	-
		Daily	-	-	-0.027	-1.7	-
		Weekend Daily	-	-	-0.043	-2.74	-
Track C	Rate Period	Peak	2.33	-0.635	-	-35.03	-27.23
		Off-peak	1.26	0.044	-	3.19	3.52
		Daily	1.43	-0.059	-	-9.85	-4.17
		Weekend Daily	1.34	0.016	-	4.1	1.2
	Elasticity	Substitution	-	-	0.077	10.61	-
		Tech. Impact-Substitution	-	-	0.214	24.04	-
		Daily	-	-	-0.044	-3.49	-
		Tech. Impact-Daily	-	-	-0.019	-3.49	-
		Weekend Daily	-	-	-0.041	-4.12	-

Notes:

[1] Estimations are based on average customer approach.
[2] Track A analysis was conducted for summer 2004.
[3] Track C analysis pools summers 2003 and 2004 and estimates a single model.

- As shown in Table 4, Track A customers reduced their peak-period energy use on critical days by about 16 percent (about 25 percent higher than the CPP-F rate impact). Track C customers reduced their peak-period use on critical days by about 27 percent.
- A comparison of the CPP-F and the CPP-V results shows that usage impacts are significantly larger with an enabling technology than without it.

4. COLORADO- XCEL ENERGY TOU PILOT[19]

In the summer of 2006, Xcel Energy initiated a pilot program that tested the impact of TOU and CPP rates, as well as enabling technologies, on consumption in the Denver metropolitan area. The effective treatment period lasted about a year, from July 15, 2006 through July 15, 2007. Approximately 3,700 residential customers initially volunteered into the pilot program. Approximately 26 percent of those customers left the pilot by the end, leaving a final sample of

[19] Based on Energy Insights, Inc, (2008a) and (2008b).

about 2,900 participants.[20] All customers had interval meters installed prior to the pilot program which could wirelessly transmit consumption to mobile vehicles collecting the household data. Some customers were offered enabling technologies—AC cycling switches and Programmable Communicating Thermostats (PCT)—in addition to the tested rate structures. Customers were subject to one of the three rate options:

- Time-of-use (RTOU): Higher price during on-peak periods and a lower price during off-peak periods
- Critical peak (RCPP): Critical peak prices up to 10 summer days; lower off-peak prices at all other times and notification of critical peak days by 4 pm the day before.
- Time-of-use+ critical peak (RCTOU): Higher on-peak price (lower than the RTOU on-peak prices), lower off-peak prices, and critical peak prices up to 10 summer days

Table 5 illustrates the demand response impacts from the treatment groups during critical peak, on-peak, and off-peak hours in the summer months of pilot period.[21] All results presented below were determined to be statistically significant. Participants subject to critical peak pricing reduced demand during peak hours substantially more so than customers not subject to CPP. Nevertheless, all groups experienced some reduction in demand. It is important to note that the results of the experiment may be subject to self-selection bias given the nature of the process through which they were recruited. Thus, the results may not generalize to the population at large.

Table 5- Demand Response Impacts

[20] The report notes that, because customers who want to participate are included in the pilot, there is an inherent self selection bias involved.

[21] As defined above, the summer months of the pilot included June, July, August, and September. As the pilot started in July of 2006 and ended in July of 2007, impacts were not measured for the months of June of 2006, and August and September of 2007.

Rate	Enabling Technology	Central AC	Critical Peak	On Peak	Off Peak
TOU	None	No	-	-10.6%	-3.0%
TOU	None	Yes	-	-5.2%	-0.3%
CPP	None	No	-31.9%		-0.1%
CPP	None	Yes	-38.4%		0.6%
CPP	AC Switch	Yes	-44.8%		1.3%
CTOU	None	No	-15.1%	-2.5%	8.7%
CTOU	None	Yes	-28.8%	-8.2%	3.6%
CTOU	AC Switch	Yes	-46.9%	-10.6%	4.0%
CTOU	PCT	Yes	-54.2%	-10.3%	3.0%

Xcel Energy notes in the conclusion to its report that the pilot was conducted as a proof of concept rather than a technology test.[22] While the demand reduction was significant, the meters implemented in the pilot were too expensive to make the offerings cost-effective.

5. FLORIDA- THE GULF POWER SELECT PROGRAM[23]

In 2000, Gulf Power, a subsidiary of the Southern Company, started a unique demand response program that provides customers with three different service options. The first option is a standard residential service (RS) pricing option which involved a standard flat rate with no time varying rates. The second optional is a conventional TOU pricing option (RST) with two pricing periods. The third option is the Residential Service Variable Price (RSVP) pricing option which is a three-period CPP tariff.

Under the RSVP option, Gulf Power provides the price signals and customers modify their usage patterns through a combination of the price signals and advanced metering and appliance control. Gulf Power markets the RSVP option under the GoodCents Select program and charges the participants a monthly participation fee. By the end of 2001, approximately 2,300 homes were served by the RSVP. Table 6 shows the rates under the Gulf Power demand response program.

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22 Energy Insights, Inc. (2008b).

23 See Appendix B of Borenstein, Jaske, and Rosenfeld (2002), which is adapted from Levy, Abbott and Hadden (2002).

Table 6- Residential Tariffs for Summer Months

Program	Period	Charge	Applicable
RS	Base	$0.057/kWh	All hours
RST	Off-peak	$0.027/kWh	12 a.m.-12 p.m. and 9 p.m.-12 a.m.
RST	Peak	$0.104/kWh	12 p.m.- 9 p.m.
RSVP	Off-peak	$0.035/kWh	12 a.m.-6 a.m. and 11 p.m.-12 a.m.
RSVP	Mid-peak	$0.046 /kWh	6 a.m.-11 a.m. and 8 p.m.-11 p.m.
RSVP	Peak	$0.093/kWh	11 a.m.-8 p.m.
RSVP	CPP	$0.29/kWh	When called

Gulf Power reports the base coincident peak demand as 6.1 KW per household (hh). RSVP program performance results presented in Table 7 show that program participants reduce their demand by 2.75 KW per household during the critical peak period or a 41 percent reduction in energy usage during the critical peak period.

Table 7- RSVP Program Performance by Period

Impact Type	Period	Impact
Average Demand Reduction	Peak	2.1 kW/hh
	Critical Peak	2.75 kW/hh
Average Energy Reduction	Peak	22%
	Critical Peak	41%

6. FRANCE- ÉLECTRICITÉ DE FRANCE (EDF) TEMPO PROGRAM[24]

Électricité de France (EDF) initiated the Tempo program in 1996. This is a full-scale voluntary program and is not a controlled experiment. The rate design entails two pricing periods, peak and off-peak and three day types. The peak period is 16 hours long, from 6 am to 10 pm, and the off-peak period is 8 hours long. Under the program, the year is divided into three day-types. *Blue days* are the least expensive 300 days, *white days* are moderately priced 43 days, and the red days are the most expensive 22 days.

[24] For a recent presentation, see Giraud (2004). For earlier analysis, see Giraud and Aubin (1994) and Aubin, Fougere, Husson and Ivaldi (1995). For the current tariff, consult http://www.edf-bleuciel.fr/accueil/mon-quotidien-avec-bleu-ciel-d-edf/option-tempo-41090.html&onglet=5.

Customers learn which day would be in effect the next day through the use of several resources including the web, call-centers, subscription to e-mail alerts and by plugging in an electrical device. EDF implemented a pilot program before launching the Tempo rate on a full-scale basis. The pilot program set prices that were much higher than the Tempo prices. The own-price elasticity for peak demand was estimated at -0.79, much higher than any of the estimates for U.S. pilots, and the own-price elasticity for off-peak usage was estimated to be -0.18.[25]

7. IDAHO- IDAHO RESIDENTIAL PILOT PROGRAM[26]

Idaho Power Company initiated two residential pilot programs in the Emmett area of Idaho in the summer of 2005 and the summer of 2006: Time-of-day (TOD) and Energy Watch (EW).

Time-of-Day Pilot

The TOD pilot was designed as a conventional TOU program where the participants were charged different rates by time of the day as shown in Table 8. The TOD pilot included 85 treatment and 420 control group customers as of August 2006.

Table 8- Rate Design for the Time-of-Day Pilot

Period	Charge	Applicable
On-Peak	$0.083/kWh	Weekdays from 1pm to 9pm
Mid-Peak	$0.061/kWh	Weekdays from 7am to 1pm
Off-Peak	$0.045/kWh	Weekdays from 9pm to 7am and all hours on weekends and holidays

The results from the TOD pilot for the summer of 2006 revealed that, on average, the peak period percentage of total summer usage was the same for the treatment and control groups – about 22 percent. In fact, the percentage of usage during the mid-peak and off-peak periods was also the same between the two groups. This indicates that the TOD rates had no effect on

25 Matsukawa (2001) found similarly high price elasticities using data on 279 households in Japan. For households with electric water heaters, he estimated an own-price elasticity of -0.768 for the peak period -0.561 for the off-peak period. Similar estimates were obtained for households without electric water heaters and for households on standard rates. Filippini (1995) also found price elasticities in this range using Swiss data.

26 Idaho Power Company (2006).

shifting usage. However, in light of the very low ratio of on-peak to off-peak rates (about 1.84), this result is not so surprising. It suggests that a higher ratio of peak to off-peak rates is needed to induce customers to shift usage from peak to off peak periods.

Energy Watch Pilot

The Idaho Power Company Energy Watch (EW) pilot was designed as a CPP pilot where the participants were notified of the CPP event on a day-ahead basis. A total of 10 EW days were called during the summer of 2006. EW featured CPP hours from 5 p.m. to 9 p.m., day-ahead notification, a CPP energy price of $0.20/kWh and a non-CPP energy price of $0.054/kWh. The EW pilot included 68 treatment and 355 control group customers as of August 2006.

Table 9 shows the reduction in load (kW) on CPP days for each of the event days. Average hourly demand reduction ranged from 0.64 kW (on June 29) to 1.70 kW (on July 27). Average hourly load reduction for all ten event days was 1.26 kW. The average total load reduction for a 4-hour event was 5.03 kW.

Table 9- Energy Watch Day: Load Reductions (kW) On Each of the Ten Event Days

Hour Beginning	Hour Ending	29-Jun	11-Jul	14-Jul	18-Jul	19-Jul	25-Jul	27-Jul	3-Aug	9-Aug	15-Aug	Average
5pm	6pm	0.64	1.31	1.09	1.39	1.2	1.33	1.58	1.14	0.83	1.02	1.17
6pm	7pm	0.69	1.5	1.17	1.43	1.32	1.45	1.62	1.27	1.14	1.15	1.29
7pm	8pm	0.77	1.58	1.16	1.57	1.41	1.55	1.7	1.24	1.02	0.96	1.33
8pm	9pm	0.8	1.48	1.11	1.47	1.27	1.4	1.6	1.13	0.95	0.89	1.25
4-Hour Total		2.89	5.87	4.53	5.85	5.2	5.74	6.5	4.77	3.94	4.02	5.03
Average Hourly		0.72	1.47	1.13	1.46	1.3	1.43	1.62	1.19	0.99	1.01	1.26
Min Temp		68	65	65	61	62	75	68	59	62	67	65
Max Temp		85	100	98	94	98	99	104	92	85	92	95
Avg Temp		75	84	83	79	80	87	87	76	73	80	80

8. ILLINOIS- ENERGY SMART PRICING PLAN

The Community Energy Cooperative's ("CEC") Energy-Smart Pricing Plan (ESPP) was the first large-scale residential real-time pricing (RTP) program in the U.S. It took place in the service territory of Commonwealth Edison in northern Illinois and ran between 2003 and 2006. ESPP initially included 750 participants and expanded to nearly 1,500 customers in 2005. The same number of participants was maintained for the 2006 program year. ESPP focused on low cost technology and tested the hypothesis that major benefits may result from RTP without the adoption of expensive technology.

The ESPP design included day-ahead announcement of the hourly electricity prices for the next day (on the day of the event, customers were charged the hourly prices that had been posted the day before), high-price day notification via phone or email when the price of electricity climbed over $0.10 per kWh (in 2006, the notification threshold was set to above $0.13 per kWh), and a price cap of $0.50 per kWh for participants meaning that the maximum hourly price is set at $0.50 per kWh during their participation in the program. In 2005 (continued in 2006), cycling switches for central air conditioners were installed at participants homes, which effectively reduced energy consumption by AC units during high price periods. In 2006, the Energy PriceLight, a glass orb similar in design to the Energy Orb used by several utilities, was distributed. The Energy PriceLight is a glass orb that receives wireless price information and relays this information, i.e. high or low electricity prices, by glowing in different colors.

Pilot Program Results for 2005[27]

The main goals of the pilot were to determine the price elasticity of demand and the overall impact on energy consumption. A regression analysis using a simple double-log specification with hourly usage as the dependent variable and hourly price and weather as the independent variables was used to estimate the price elasticity of demand for the summer months. Overall, the price elasticity during the summer of 2005 was estimated to be -0.047.

With enabling technology, i.e. automatic cycling of the central-air conditioners during high-price periods, the overall price elasticity increased to -0.069. The largest response occurred on high-price notification days. For instance, on the day with the highest prices during the summer of 2005, participants reduced their peak hour consumption by 15 percent compared to what they would have consumed under the flat ComEd residential rate. Price responsiveness varied over the course of a day. Own price elasticities ranged from -0.02 (daytime) to -0.05 (evening and high price notification periods)

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27 Summit Blue Consulting (2006).

The impact analysis indicated that ESPP participants consumed 35.2 kWh less per month during the summer months compared to what they would have consumed without the ESPP. These savings represented roughly three to four percent of summer electricity usage. Statistically significant savings were not found for winter usage which is not surprising since most high price days occur in the summer months in this area. Overall, ESPP resulted in a net decrease in monthly energy consumption.

Pilot Program Results for 2006[28]

Results from the analysis of the ESPP in 2006 supported the findings of program's previous years. The price elasticity during the summer of 2006, for hours when the price of electricity was equal to or below $0.13 per kWh, was estimated to be -0.047. The price elasticity for the same period, but for hours when the price of electricity was above $0.13 per kWh, was estimated to be -0.082. The Energy PriceLight improved customer responsiveness resulting in an elasticity of -0.067 across all hours. For customers with A/C cycling, the price elasticity for high price periods was estimated at -0.098.

Results of the energy impact analysis indicated that ESPP participants consumed 16.7 kWh less per month, year round, relative to individuals not on the ESPP rate. During the summer months, participants consumed an additional 10.0 kWh less per month, or equivalently 26.7 kWh less per month total. This translates to approximately three percent of summer electricity usage, similar to the savings results of the 2005 program year. Again, on the whole, ESPP resulted in a decrease in monthly energy consumption.

9. MISSOURI- AMERENUE CRITICAL PEAK PRICING PILOT

First Year of the Pilot Program (2004)[29]

AmerenUE in association with the Missouri Collaborative formed by the Office of Public Counsel (OPC), the Missouri Public Service Commission (MPSC), the Department of Natural Resources (DNR) and two industrial intervener groups initiated a residential TOU pilot study in Missouri during the spring of 2004. Program impacts associated with three different TOU

[28] Summit Blue Consulting, (2007).
[29] RLW Analytics, (2004).

programs were evaluated: TOU with peak, mid-peak and off-peak periods; TOU with a CPP component; and TOU with a CPP component and an enabling technology (smart thermostat). Table 10 shows the pilot rates.

Table 10- Residential TOU Experiment Summer Rate Design

Program	Time	Charge	Applicable
TOU	Off Peak	$0.048/kWh	Weekday 10pm–10am, weekends, holidays
TOU	Mid Peak	$0.075/kWh	Weekdays 10am– 3pm and 7pm-10pm
TOU	Peak	$0.183/kWh	Weekdays 3pm – 7pm
TOU-CPP	Off Peak	$0.048/kWh	Weekdays 10pm–10am, weekends, holidays
TOU-CPP	Mid Peak	$0.075/kWh	Weekdays 10am– 3pm and 7pm-10pm
TOU-CPP	Peak	$0.168/kWh	Weekdays 3pm – 7pm
TOU-CPP	CPP	$0.30/kWh	Weekdays 3pm – 7pm, 10 times per summer

Table 11 shows the number of participants in the treatment and control groups by rate type.

Table 11- Experiment Sample Design

Treatment	Treatment Sample Size	Control Sample Size
TOU	88	89
TOU-CPP	85	89
TOU-CPP-Tech	77	117
Total	250	295

Summer 2004 results show that the participants in the TOU and TOU-CPP groups did not shift a statistically significant amount of load from the on-peak to off-peak or mid-peak periods. Off-peak consumption increased and peak consumption decreased only slightly for the treatment groups compared to the control groups for both TOU and TOU-CPP programs, but these differences were not statistically significant. On the critical event days, the TOU-CPP and TOU-CPP-Tech groups respectively reduced their average CPP period loads by 12 and 35 percent, compared to the control group. Both impacts are statistically significant at the five percent level.

Second Year of the Pilot Program (2005)[30]

During the second year of the pilot, the first year rate design was maintained. In the summer of 2005, the load shifting impacts were once again insignificant for the TOU and TOU-CPP

[30] Voytas (2006).

treatments on the non-event days. However, the TOU-CPP and TOU-CPP-Tech customers reduced their CPP period usages by 13 and 24 percent respectively on the event days similar to those in the summer of 2004. These reductions were statistically significant.

10. New Jersey- GPU Pilot[31]

GPU offered a residential TOU pilot program with a critical peak price and enabling technology component in the summer of 1997. The rate design involved three price tiers (peak, shoulder, and off-peak) and a critical peak price that is only effective for a limited number of high-cost summer hours. Moreover, the pilot program tested the impacts from two sets of alternative rates by allocating treatment customers to two groups and subjecting each group to one of the two sets. Table 12 shows the control and treatment group rate designs.

Table 12- Experimental Rate Design

Group	Charge	Applicable
Control	Standard increasing-block residential tariff: $0.12/kWh if consumption <=600kWh per month $0.153/kWh if consumption >600kWh per month	All hours
Treatment Group 1 (High shoulder/peak design)	Off-peak: $0.065/kWh	1a.m.-8a.m. and 9p.m.-12p.m. weekdays; All day on weekends and holidays.
	Shoulder:$0.175/kWh	9a.m.-2p.m. and 7p.m.-8p.m. weekdays.
	Peak:$0.30/kWh	3p.m.-6p.m. weekdays
	Critical:$0.50/kWh	When called during peak period
Treatment Group 2 (Low shoulder/peak design)	Off-peak:$0.09/kWh	1a.m.-8a.m. and 9p.m.-12p.m. weekdays; All day on weekends and holidays.
	Shoulder:$0.125/kWh	9a.m.-2p.m. and 7p.m.-8p.m. weekdays.
	Peak:$0.25/kWh	3p.m.-6p.m. weekdays
	Critical:$0.50/kWh	When called during peak period

One important feature of this pilot is that communication equipment was installed in customer premises allowing them to preset their set points during the critical periods. Analysis of the hourly load data for each of the treatment and control group customers collected for the period of June through September 1997 revealed the following results: On non-critical weekdays, the

[31] Braithwait (2000).

largest usage reductions in the average hourly load were observed during the peak period and averaged to 0.53 KW or 26 percent relative to the control group. Load reductions were also observed during the late-morning shoulder period, but these reductions were limited compared to those during the peak period. The treatment group with the high rate design reduced usage by roughly 50 percent more during each of peak and shoulder periods than the treatment group with the low-rate design. On CPP days, the results were similar to those on the non-CPP weekdays; though larger in magnitude, especially during the peak period. In the first hour of the peak period, average load reduction was 1.24 KW or a 50 percent reduction compared to the control group. During the next two peak hours, the reduction was around 1 KW, later falling to 0.59 KW on the last peak hour. Also, the treatment group usage was substantially larger than the control group during the shoulder and off-peak periods following the critical peak hours.

On weekends, average usage was similar for the control and treatment customers, with slightly lower (though not statistically significant) levels for the treatment customers. Average usage over all days by the treatment group decreased compared to the control group, but the result was not statistically significant. A large portion of these reductions can be attributed to the changes in the weekday usage.

The data were also used to estimate the elasticity of substitution using two alternative models: the constant elasticity of substitution (CES) model discussed later in this paper and the more flexible generalized Leontief (GL) model. The substitution elasticity from the CES model was estimated to be 0.30. This estimate was larger than the 0.14 value estimated by EPRI in its analysis of the best five TOU pricing experiments from the late 1970s/early 1980s. The larger substitution elasticity from this pilot can be attributed to the presence of interactive communication equipment through which the customers preset their usage patterns of air conditioning (AC) and other appliances. The GL model allows substitution elasticity estimates to vary by time-period. With this model, the substitution elasticity between peak and off-peak periods was estimated as 0.40, or a third higher than the estimate from the CES model.

11. NEW JERSEY- PSE&G RESIDENTIAL PILOT PROGRAM [32]

Public Service Electric and Gas Company (PSE&G) offered a residential TOU/CPP pilot pricing program in New Jersey during 2006 and 2007. The PSE&G pilot had two sub-programs. Under the first sub-program, *myPower Sense*, participants were educated about the TOU/CPP tariff and were notified of the CPP event on a day-ahead basis. The program assessed the reduction in energy use when a CPP event was called. Under the second sub-program, *myPower Connection*, participants were given a free programmable communicating thermostat (PCT) that received price signals from PSE&G and adjusted their air conditioning settings based on previously programmed set points. A total of 1,148 customers participated in the pilot program; 450 in the control group, 379 in *myPower Sense*, and 319 in *myPower Connection*. PSE&G recruited the participants separately for each group through direct mail with follow-up telemarketing[33]. Customers didn't have the opportunity to choose the treatment they would be receiving. *myPower Sense* customers received a $25 incentive upon enrollment and another $75 was paid upon the conclusion of the program. *myPower Connection* participants were provided free PCTs and received $75 at the end of the program. The TOU/CPP tariff included a night discount, a base rate, an on-peak adder, and a critical peak adder for the summer months as shown in Table 13.

Table 13- TOU/CPP Rate Design: Summer Months (June to September 2006 and 2007)

Period	Charge (June to September 2006)	Charge (June to September 2007)	Applicable
Base Price	$0.09/kWh	$0.087/kWh	All hours
Night Discount	-$0.05/kWh	-$0.05/kWh	10 p.m.-9 a.m. daily
On Peak Adder	$0.08/kWh	$0.15/kWh	1 p.m.-6 p.m. weekdays
Critical Peak Adder	$0.69/kWh	$1.37/kWh	1 p.m.-6 p.m. weekdays when called (Added to the base price when called)

PSE&G called two CPP events in Summer 2006 and five CPP events in Summer 2007. The results show that *myPower Connection* customers reduced their peak demand by 21 percent due to TOU-only pricing. These customers reduced their peak load by an additional 26 percent on CPP event days. *myPower Sense* customers with CAC ownership reduced their peak demand by

32 PSE&G and Summit Blue Consulting, (2007).

33 PSE&G recruited pilot participants from Cherry Hill and Hamilton towns as they had high percentages of residents on standard rates and high rates of customer ownership of central air conditioning systems.

three percent on TOU-only days. On CPP event days, their peak load reductions reached 17 percent. Interestingly, *myPower Sense* customers without CAC ownership achieved six percent peak reductions on TOU-only days while the reductions reached 20 percent on CPP event days. As expected, *myPower Connection* customers reduced their peak-demand consistently more than *myPower Sense* customers because they had the PCT enabling technology.

The study also estimated summer substitution elasticities for *myPower Connection and myPower Sense* customers. Table 14 presents the elasticity estimates and the associated lower and upper bounds for 90 percent confidence level. As expected, *myPower Connection* customers have the largest elasticity of substitution, followed respectively by *myPower Sense* customers with and without CAC ownership.

Table 14- Estimated Substitution Elasticity for Summers 2006 and 2007

Impact Estimate	Substitution Elasticity	90% Confidence Interval
myPower Connection	0.13	0.12 to 0.13
myPower Sense with CAC	0.07	0.06 to 0.08
myPower Sense without CAC	0.06	0.06 to 0.07

12. New South Wales/Australia- Energy Australia's Network Tariff Reform [34]

The TOU pricing program is the largest demand management project by Energy Australia. In 2006, the TOU results showed that residential customers achieved slight energy conservation effects. These conservation effects were larger in the winter than in the summer for the residential customers. Business customers were not found to be price-responsive to the TOU prices.

Energy Australia also started the Strategic Pricing Study in 2005 which included 1,300 voluntary customers (50 percent business, 50 percent residential customers). The study tested seasonal, dynamic, and information only tariffs and involved the use of in-house displays and online

[34] Colebourn (2006).

access to data. Study participants received dynamic peak price signals through Short Message Service (SMS), telephone, email, or the display unit.

Preliminary results that are available from three dynamic peak pricing (DPP) events showed that the residential customers reduced their dynamic peak consumption by roughly 24 percent for DPP high rates (A$2+/kWh) and roughly 20 percent for DPP medium rates (A$1+/kWh). Response to the 2nd DPP event was greater than that to the 1st DPP event. This may be attributed to the day-ahead notification under the 2nd DPP event (versus day-of notification under the 1st DPP event) and/or temperature differences. Response to the 2nd event was also greater than to the 3rd DPP event. This may be explained by lower temperatures on the 3rd DPP event which may have led to less discretionary appliances to turn off.

13. Ontario/Canada- Ontario Energy Board's Smart Price Pilot[35]

The Ontario Energy Board operated the residential Ontario Smart Price Pilot (OSPP) between August 2006 and March 2007. The OSPP used a sample of Hydro Ottawa residential customers and tested the impacts from three different price structures:

- The existing Regulated Price Plan (RPP) TOU: Off-peak rates were set at C$0.035 per kWh, mid-peak rates were set at C$0.075 per kWh, and on-peak rates were set at C$0.105 per kWh
- RPP TOU rates with a CPP component (TOU CPP): The CPP was set at C$0.30 per kWh based on the average of the 93 highest hourly Ontario electricity prices in the previous year. The RPP TOU off-peak price was decreased to C$0.031 (from C$0.035) per kWh to offset the increase in the critical peak price. The maximum number of critical day events was set at nine days, however only seven CPP days were called during the pilot.
- RPP TOU rates with a critical peak rebate (TOU CPR): The CPR provided participants with a C$0.30 per kWh rebate for each kWh of reduction from estimated baseline consumption. The CPR baseline consumption was defined as the average usage during the same hours over the participants' last five non-event weekdays, increased by 25 percent.

[35] Ontario Energy Board, (2007).

A total of 373 customers participated in the pilot: 124 in the TOU-only, 124 in the TOU-CPP, and 125 in the TOU-CPR group. The control group included 125 participants who had smart meters installed but continued to pay non-TOU rates.

The OSPP results show that the load shift during the critical hours of the four summer CPP events ranged between 5.7 percent and 25.4 percent.[36] They also showed that the load shift during the entire peak period of the four summer CPP events ranged between 2.4 percent and 11.9 percent. This study also analyzed the total conservation impact during the full pilot period. The average conservation impact across all customers was estimated to be six percent.

14. Washington (Seattle Suburbs)- Puget Sound Energy (PSE)'s TOU Program[37]

PSE initiated a TOU program for its residential and small commercial customers in 2001. The rate design involved four price periods. Prices were most expensive during the morning and evening periods with mid-day and economy periods following these most expensive periods. Some 300,000 PSE customers were placed in the program and given the option to go back to the standard rates if they were not satisfied with the program. The peak price was roughly 15 percent higher than the average price that prevailed before the program and the off-peak price was 15 percent lower. In 2002, the second year of the program, customers were charged a monthly fee of $1 per month for meter-reading costs. The results of PSE's quarterly report revealed that the 94 percent of the customers paid an extra $0.80 (the total of $0.20 power savings and $1 meter reading costs) by participating in the pilot. This was in contrast with the first year results where customers were not charged meter reading costs and around 55 percent of them experienced bill savings. As a result of customer dissatisfaction and negative media coverage, PSE ceased its TOU program.

Several lessons can be derived from this experience. First, modest price differentials between peak and off-peak may induce customers to shift their load if they are accompanied with unusual circumstances such as the energy crisis of 2000-2001 in the West. An independent analysis of the program found that customers lowered peak usage by five percent per month over a 15 month

[36] Under the OSPP, 3 to 4 hours of the peak period were defined as critical on a CPP day.
[37] Faruqui and George (2003).

period, with reductions being slightly higher in the winter months and slightly lower in the summer months. It is important to provide the customers with accurate expectations about their bill savings. The pilot over-promised savings and when these did not materialize, there was a significant backlash against the very premises of the program and the intentions of the utility. Finally, it is essential to offer a pilot program before implementing a full-scale program.

15. WASHINGTON- THE OLYMPIC PENINSULA PROJECT[38]

The Olympic Peninsula Project was a component of the Pacific Northwest GridWise Testbed Demonstration that took place in Washington and was led by the Pacific Northwest National Laboratory (PNNL). The Peninsula Project tested whether automated two-way communication systems between grid and passive resources (i.e., end use loads and idle distributed generation) and the use of price signals as instruments would be effective in reducing the stress on the system. Our review focuses on the residential response and does not cover the impacts associated with the distributed generation resources.

By the end of 2005, the project recruited participants with the assistance of the local utility companies. The project received a mailing list from the utilities of the potential participants who had high-speed internet, electric HVAC systems, electric water heater, and electric dryer. Letters were mailed to these customers to recruit potential participants. At the end of the recruiting process, 112 homes were installed with the two-way communication equipments that allowed utilities to send the market price signals to the consumers and allowed consumers to pre-program their demand response preferences. These residential participants were then evenly divided into three treatment groups and a control group. Equipment was also installed in the control group homes but they were given no additional information.

Each treatment group was assigned to one of the three electricity contracts: Fixed-prices that were constant across time; time-of-use/critical peak prices (TOU/CPP); and real time prices. In the last category, participants were able to program their appliance preferences over the web but they still had the option to override their preferences at any time.

[38] Pacific Northwest National Laboratory (2007).

Table 15 shows the prices that prevailed under fixed price and TOU/CPP contracts.

Table 15- Experimental Rate Design

Contract	Season	Period	Charge	Applicable
Time-of-Use/ CPP	Spring (1 Apr-24 Jul) and Fall/Winter (1 Oct-31 Mar)	Off-peak	$0.04119/kWh	9 am-6pm and 9pm-6am
		On-peak	$0.1215/kWh	6am-9am and 6pm-9pm
		Critical	$0.35/kWh	Not called
	Summer (25 Jul- 30 Sep)	Off-peak	$0.05/kWh	9am-3pm
		On-peak	$0.135/kWh	3pm-9pm
		Critical	$0.35/kWh	When called
Fixed-Price	All seasons	All day	$0.081/kWh	All hours

The fixed-price group saved two percent on their average monthly bill compared to the control group; the TOU group saved 30 percent and the RTP group saved 27 percent. Differences in average energy consumption between the contract groups were small but statistically significant. The TOU group consumed 21 percent less energy and achieved conservation benefits from time-of-use pricing. The RTP group consumed as much as the control group. The fixed-price group used four percent more energy than the control group.

Examination of the residential load shapes by contract and season revealed that the time-of-use/CPP contract was the most effective design at reducing peak-demand. On average, the real-time contract did not bring about the lowest average peak demand. Preliminary analysis of the data reveals that peak demand consumption fell by 15 to 17 percent for RTP group, while it fell by 20 percent for the TOU/CPP group relative to the fixed price group.[39]

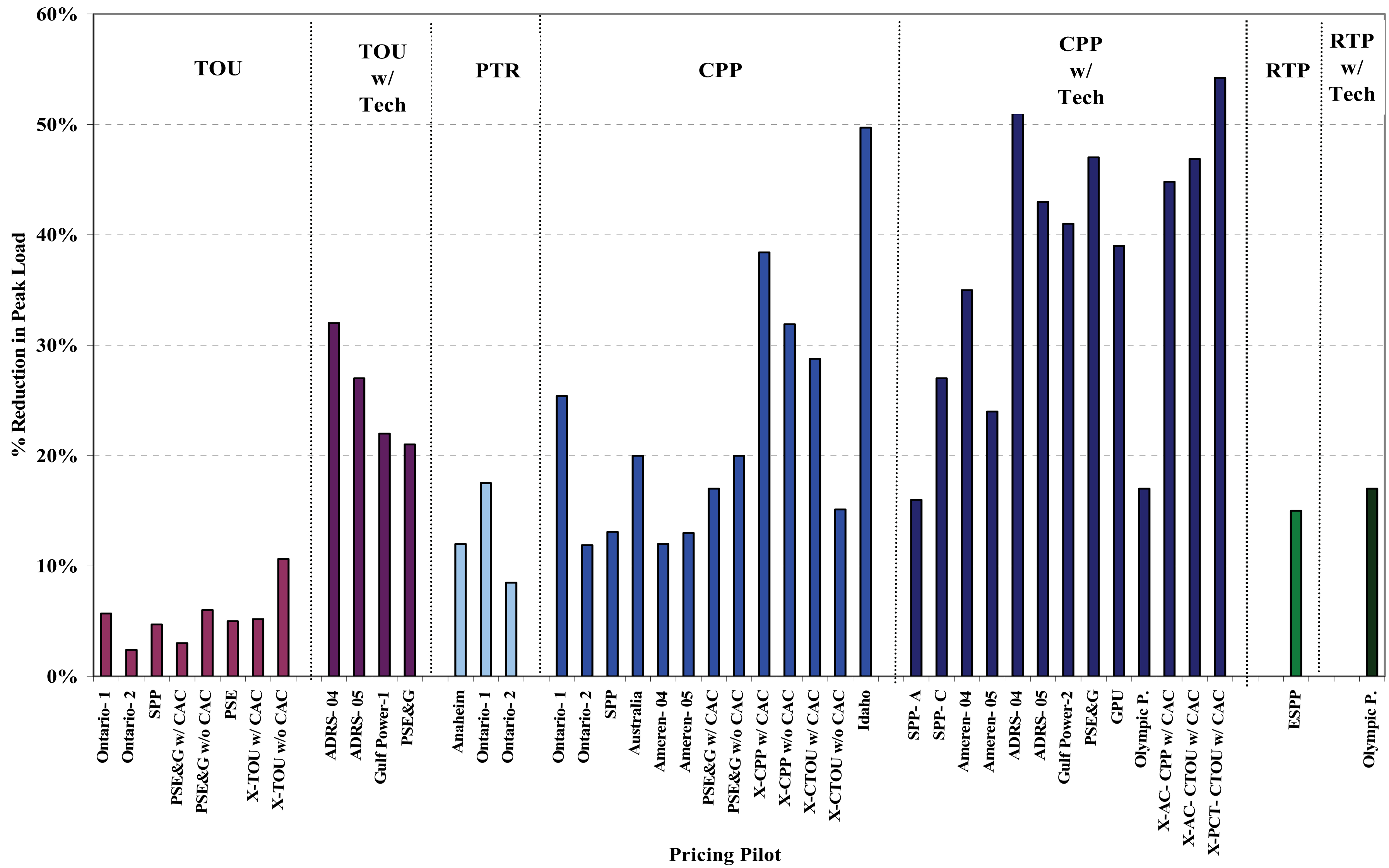
2.2. CROSS-EXPERIMENTAL ASSESSMENT

Our review of the 15 pricing experiments reveals that the demand response impacts from different pilot programs vary widely due to the difference in the rate designs tested, use of

[39] Kiesling (2008).

enabling technologies, ownership of central air conditioning and more generally, due to the variations in sample design. Figure 1 presents a summary.

Figure 1: Summary of the Demand Impacts



Notes:

*Percentage reduction in load is defined relative to different bases in different pilots. The following notes are intended to clarify these different definitions.

1. TOU with Technology (TOU w/ Tech) and CPP with Technology (CPP w/ Tech) refer to the pricing programs that had some form of enabling technologies.
2. TOU program impacts are defined relative to the usage during peak hours unless otherwise noted.
3. CPP program impacts are defined relative to the usage during peak hours on CPP days unless otherwise noted.
4. Ontario- 1 refer to the percentage impacts during the critical hours that represent only 3-4 hours of the entire peak period on a CPP day. Ontario- 2 refer to the percentage impacts of the programs during the entire peak period on a CPP day.
5. TOU impact from the SPP is based on the CPP-F treatment effect for normal weekdays on which critical prices were not offered.
6. ADRS- 04 and ADRS- 05 refer respectively to the 2004 and 2005 impacts. ADRS impacts on non-event days are represented in the TOU with Technology section.
7. CPP impact for Idaho is derived from the information provided in the reviewed study. Average of kW consumption per hour during the CPP hours (for all 10 event days) is approximately 2.5 kW for a control group customer while this value is 1.2 kW for a treatment group customer. Percentage impact from the CPP treatment is calculated as 50%.
8. Gulf Power-1 refers to the impact during peak hours on non-CPP days and therefore shown in the TOU with Technology section while Gulf Power- 2 refers to the impact during CPP hours on CPP days.
9. Ameren- 04 and Ameren- 05 refer to the impacts respectively from the summers of 2004 and 2005.
10. SPP- A refers to the impacts from the CPP-V program on Track A customers. Two thirds of Track A customers had some form of enabling technologies.
11. SPP- C refers to the impacts from the CPP-V program on Track C customers. All Track C customers had smart thermostats.
12. X-CPP program only differentiates between CPP and non-CPP hours while X-CTOU program differentiates between CPP, on-peak, and off-peak hours.

To synthesize the information from the 15 pricing experiments, we have constructed a dataset of 28 observations where the impacts are grouped with respect to the rate designs and the existence of an enabling technology. Table 16 provides the mean impact estimates and the 95 percent confidence intervals associated with the mean values from this dataset.

Table 16- Summary Impacts

Rate Design	Number of Observations	Mean	95% Lower Bound	95% Upper Bound	Min	Max
TOU	5	4%	3%	6%	2%	6%
TOU w/ Technology	4	26%	21%	30%	21%	32%
PTR	3	13%	8%	18%	9%	18%
CPP	8	17%	13%	20%	12%	25%
CPP w/ Technology	8	36%	27%	44%	16%	51%

Notes:

1. Confidence intervals are calculated assuming normal distribution of the impact estimates.
2. The pilot results from Xcel Energy are excluded from the summary statistics due to the role of self-selection bias, as reported in the study, in driving the large demand impacts.
3. The CPP impact for Idaho is also excluded from the summary statistics since it is an outlier.

On average, TOU programs are associated with a mean reduction of four percent in peak usage, and a 95 percent confidence interval ranges from *three to six percent*. CPP programs reduce peak usage by 17 percent and a 95 confidence interval ranges from *13 to 20 percent*. CPP programs supported with enabling technologies reduce peak usage by 36 percent and a 95 confidence interval ranges from *27 to 44 percent*. Impacts associated with PTR and TOU supported with enabling technology programs are also provided in Table 16. However, all these results should be interpreted with caution due to the small number of observations underlying the distributions. Nine out of the twelve impact estimates with enabling technologies are tested on customers with CAC ownership, so these impacts also capture impacts due to CAC ownership.

Our survey finds that in addition to displaying a wide variation in the size of impacts due to different rate designs, impacts also vary widely among the experiments using the same rate design. The residual variation comes from variation in price elasticities and in sample design. Substitution elasticities from the experiments range from 0.07 to 0.40 while the own price elasticities range from -0.02 to -0.10. Availability of the enabling technologies, ownership of central air conditioning and the type of the days examined (weekend vs. weekday) are some of the factors that lead to variations in the elasticities.

A question of great interest to policy makers is how the impact estimates vary with the price levels. In other words, the question is as the critical prices increase with equal increments, do the peak demand impacts also increase with equal increments? To shed light on this question, we focus on a single experiment which has a high quality design and sufficient data to carry out the simulation. We use the California SPP experiment data whose results have been codified into a widely available tool called PRISM (Price Impact Simulation Model).[40]

PRISM predicts the changes in electricity usage that are induced by time-varying rates by utilizing a constant elasticity of substitution (CES) demand system. PRISM has the capability to predict these changes for peak and off-peak hours for both critical and non-critical peak days. Moreover, PRISM allows predictions to vary by other exogenous factor such as the saturation of central air conditioning and variations in climate. The model can be set to demonstrate these impacts on different customer types. Appendix provides a brief discussion of the PRISM model.

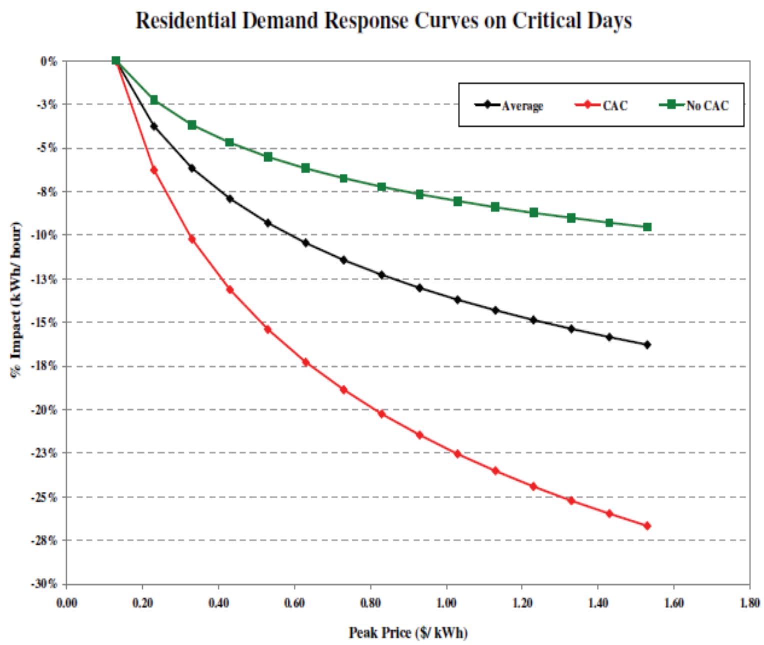
Since our purpose is to determine how the usage impacts vary as the critical prices are increased gradually, we ran the PRISM model using a set of prices shown in Figure 2. To understand the relationship between the prices and the percentage impact on load, consider the following PRISM simulation result. For the average customer, peak period energy usage decreases by 4 percent when the peak-price increases by 10 cents from \$0.13 per kWh to \$0.23 per kWh. However, peak period energy usage decreases by only 8 percent when the peak price is increased by 30 cents from \$0.13 per kWh to \$0.43 per kWh. This example demonstrates that the load impact only doubles when the price increase triples. We can also observe the differences between customer types in their price-responsiveness from these response curves. For a given

40 For model description, see Charles River Associates (2005) and Faruqui-Wood (2008). The model can be downloaded from www.eei.org/ami.

price increase, Non-CAC customers (without CAC ownership) are the least responsive group while CAC customers (with CAC Ownership) are the most responsive.

Figure 2- PRISM Simulation

How do the peak impacts vary with critical prices?



% Reduction in Quantity

Critical Price (cents/kWh)	Average Customer	Customer w/ CAC	Customer w/o CAC
0.13	0.0%	0.0%	0.0%
0.23	-3.8%	-6.3%	-2.3%
0.33	-6.2%	-10.2%	-3.7%
0.43	-7.9%	-13.1%	-4.7%
0.53	-9.3%	-15.4%	-5.5%
0.63	-10.4%	-17.3%	-6.2%
0.73	-11.4%	-18.9%	-6.7%
0.83	-12.3%	-20.2%	-7.2%
0.93	-13.0%	-21.5%	-7.7%
1.03	-13.7%	-22.5%	-8.0%
1.13	-14.3%	-23.5%	-8.4%
1.23	-14.9%	-24.4%	-8.7%
1.33	-15.4%	-25.2%	-9.0%
1.43	-15.8%	-26.0%	-9.3%
1.53	-16.3%	-26.7%	-9.5%

The response curves in Figure 2 demonstrate how the percent impact on peak demand varies with the peak-period price on critical days. These curves show that the percentage peak demand impacts increase as prices increase, but at a decreasing rate. This non-linear relation between usage impacts and prices is reflected in the concave shape of the response curves.

3. CONCLUSIONS

This article reviews the most recent empirical evidence on the effectiveness of residential dynamic pricing programs. We find that demand responses vary from modest to substantial due to a variety of factors, some of which can be controlled such as electricity prices and whether no not enabling technologies are present, and some of which cannot be controlled, such as the design of the experiment and its location. With those caveats in mind, we find that time-of-use rates induce a drop in peak demand that ranges between three to six percent and critical-peak pricing tariffs lead to a drop in peak demand of 13 to 20 percent. When accompanied with enabling technologies, the latter set of tariffs lead to a drop in peak demand in the 27 to 44 percent range.

There is need for further work on the empirical data. In particular, it would be useful to identify the best experiments and to pool their data, yielding a unified national model. However, even in the absence of a unified model, we can state with confidence that residential dynamic pricing designs can be very effective in reducing peak demand and lowering energy costs.

These results have important implications for the reliability and least cost operation of an electric power system facing ever increasing demand for power and surging capacity costs. Demand response programs that blend together customer education initiatives, enabling technology investments, and carefully designed time-varying rates can achieve demand impacts that can alleviate the pressure on the power system. Uncertainties involving the fuel prices and the form of a carbon pricing regime that is in the horizon emphasize the importance of the demand-side resources. Dynamic pricing regimes also incorporate some uncertainties such as the responsiveness of customers, cost of implementation and revenue impacts. However, these uncertainties can be addressed to a large extent by implementing pilot programs that can help guide the full-scale deployment of dynamic pricing rates.

Table 17- Summary of the Experimental Tariffs

No	Study	Control Group Tariff	Applicable Period	Treatment Group Tariff	Applicable Period
1	California- Anaheim Peak Time Rebate Pricing Experiment	$0.0675/kWh $0.1102/kWh	Usage<=240kWh per month Usage>240kWh per month	**PTR/** Control group tariff **PTR/** $0.35/kWh rebate for each kWh reduction below baseline	All hours except 12a.m.- 6p.m. on CPP days. 12a.m.- 6p.m. on CPP days.
2	California Automated Demand Response System Pilot (ADRS)	**Same as CA SPP**			
3	California- Statewide Pricing Pilot (SPP)	$0.13/kWh.	All hours	**TOU**/ Off-peak: $0.09/kWh **TOU**/ Peak: $0.22/kWh **CPP-F**/ Off-peak: $0.09/kWh **CPP-F**/ Peak: $0.22/kWh **CPP-F**/ CPP: $0.59/kWh **CPP-V**/ Off-peak: $0.10/kWh **CPP-V**/ Peak: $0.22/kWh **CPP-V**/ CPP: $0.65 /kWh	12a.m.- 2 p.m. and from 7 p.m. until 12a.m. weekdays, all day on weekends. 2 p.m. to 7 p.m. weekdays. 12a.m.- 2 p.m. and from 7 p.m. until 12a.m. weekdays, all day on weekends. 2 p.m. to 7 p.m. weekdays. 2 p.m. to 7 p.m. weekdays when called. 12a.m.- 2 p.m. and from 7 p.m. until 12a.m. weekdays, all day on weekends. 2 p.m. to 7 p.m. weekdays. 2 or 5 hours during 2 p.m. to 7 p.m., weekdays when called.
4	Xcel Experimental Residential Price Response Pilot Program	NA			
5	Florida- The Gulf Power Select Program	$0.057/kWh	All hours	**RST**/ Off-peak: $0.027/kWh **RST**/ Peak: $0.104/kWh **RSVP**/ Off-peak: $0.035/kWh **RSVP**/ Mid-peak: $0.046 /kWh **RSVP**/ Peak: $0.093/kWh **RSVP**/ CPP: $0.29/kWh	12 a.m.-12p.m. and 9p.m.-12a.m. 12p.m.- 9p.m. 12a.m.-6a.m. and 11p.m.-12a.m. 6a.m.-11a.m. and 8p.m.-11p.m. 11a.m.-8p.m. Assigned hours on CPP days.
6	Electricite de France (EDF) Tempo Program	NA			
7	Idaho- Idaho Residential Pilot Program	$0.054/kWh $0.061/kWh	Usage<= 300 kWh per month Usage>300 kWh per month	**TOU**/ Off-peak: $0.045/kWh **TOU**/ Mid-peak: $0.061 /kWh **TOU**/ On-peak: $ 0.083/kWh **CPP**/ Non-CPP hours: $0.054/kWh **CPP**/ CPP: $0.20/kWh	9p.m. to 7a.m. weekdays, all day on weekends. 7a.m. to 1p.m. weekdays. 1p.m. to 9p.m. weekdays. All hours except CPP hours. 5 p.m. to 9 p.m. on CPP days.
8	The Community Energy Cooperative's Energy-Smart Pricing Plan (ESPP)	NA			
9	Missouri- AmerenUE Residential TOU Pilot Study	NA	NA	**TOU**/ Off-peak: $0.048/kWh **TOU**/ Mid-peak: $0.075/kWh **TOU**/ On-peak: $0.1831/kWh **CPP**/ same as TOU except that there is a CPP component set at $0.30/kWh and peak price is decreased to $0.1675 /kWh	10p.m.–10a.m. weekdays, all day on weekends. 10a.m.– 3p.m. and 7p.m.-10p.m. weekdays. 3p.m. – 7p.m. weekdays. CPP days when called, otherwise same as TOU.

Table 17- (Cont'd) Summary of the Experimental Tariffs from the Studies Reviewed

No	Study	Control Group Tariff	Applicable Period	Treatment Group Tariff	Applicable Period
10	New Jersey- GPU Pilot	$0.12/kWh $0.153/kWh	Usage<=600kWh Usage>600kWh	**High-rate Design** **CPP/** Off-peak: $0.065/kWh **CPP/** Shoulder:$0.175/kWh **CPP/** Peak:$0.30/kWh **CPP/** Critical:$0.50/kWh **Low-rate Design** **CPP/** Off-peak:$0.09/kWh **CPP/** Shoulder:$0.125/kWh **CPP/** Peak:$0.25/kWh **CPP/** Critical:$0.50/kWh	1a.m.-8a.m. and 9p.m.-12p.m. weekdays, all day on weekends and holidays. 9a.m.-2p.m. and 7p.m.-8p.m. weekdays. 3p.m.-6p.m. weekdays When called during peak period 1a.m.-8a.m. and 9p.m.-12p.m. weekdays, all day on weekends and holidays. 9a.m.-2p.m. and 7p.m.-8p.m. weekdays. 3p.m.-6p.m. weekdays When called during peak period
11	New Jersey- PSE&G Residential Pilot Program	$0.087/kWh	All hours	**CPP/** Night: $0.037/kWh **CPP/** Peak: $0.24/kWh **CPP/** CPP: $1.46/kWh	10 p.m.-9a.m. daily. 1p.m.-6p.m. weekdays. 1p.m.-6p.m. weekdays when called.
12	Energy Australia's Network Tariff Reform	NA			
13	Ontario/ Canada- Ontario Energy Board Smart Price Pilot	$0.058/kWh $0.067/kWh	Usage<= 600 kWh per month Usage>600 kWh per month	**TOU/** Off-peak: $0.035/kWh **TOU/** Mid-peak: $0.075/kWh **TOU/** On-peak: $0.105/kWh **CPP/** same as TOU except that there is a CPP component set at $0.30/kWh and off-peak price is decreased to $0.031/kWh **PTR/** same as TOU with PTR at $0.30/kWh for each kWh reduction below baseline	10 p.m.- 7 a.m. weekdays, all day on weekends and holidays. 7 a.m.- 11 a.m. and 5 p.m.- 10 p.m. weekdays. 11 a.m.- 5 p.m. weekdays. CPP days when called, otherwise same as TOU. CPP days when called, otherwise same as TOU.
14	Puget Sound Energy (PSE)'s TOU Program	NA			
15	Washington - Olympic Peninsula Project	NA	NA	**Summer** **CPP/** Off-peak:$0.05/kWh **CPP/** On-peak:$0.135/kWh **CPP/** Critical:$0.35/kWh **Fall/ Spring/ Winter** **CPP/** Off-peak:$0.04119/kWh **CPP/** On-peak:$0.1215/kWh **CPP/** Critical:$0.35/kWh **Fixed Price/** All hours:$0.081/kWh	9 am-6pm and 9pm-6am 6am-9am and 6pm-9pm Not called 9am-3pm 3pm-9pm When called All hours

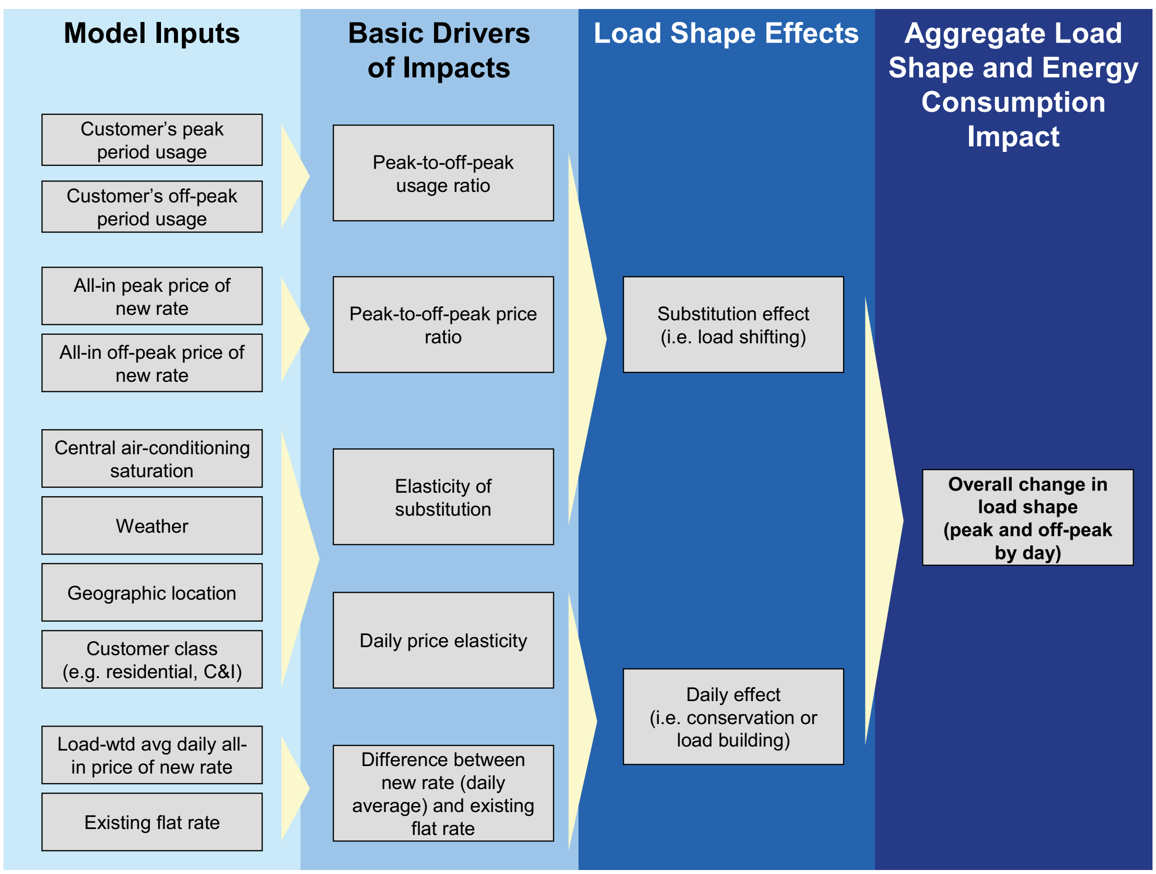
APPENDIX

1- A Primer on PRISM

The Pricing Impact Simulation Model (PRISM) was originally developed using data derived from the California Statewide Pricing Pilot (SPP) that included some 2,500 residential and small and medium sized commercial and industrial customers during 2003-2005.[41] Although it originated in California, the basic model has now been adapted to conditions in other parts of North America and the national version of PRISM is available for use by interested parties.

The PRISM includes a model for estimating "demand response impacts" and another model for estimating "financial benefits" to customers and utilities. Figure A-1 shows the PRISM Impacts Model, which is used to estimate the "unit impact" or change in consumption per customer resulting from dynamic pricing. This is the customer level demand response or the "impact" estimate.

Figure A-1: PRISM Impacts Model- Inputs and Outputs



Default demand curves and price elasticities in PRISM are based on a large data set that includes responses of approximately 2,500 customers over a two-year period to various forms of dynamic

[41] Charles River Associates, "Impact Evaluation of the California Statewide Pricing Pilot," March 16, 2005.

pricing, a wide variety of weather conditions, and a range of socio-demographic factors. Specifically, the data set used to estimate the customer demand curves and price elasticities in PRISM is based on a rigorous experimental design. Nevertheless, these elasticity estimates can easily be replaced with other elasticity values that a utility has estimated using data on its own customers or by other values that the utility has borrowed from other utilities.

The purpose of the PRISM Impacts Model is to estimate the change in consumption per customer resulting from dynamic pricing. In addition to estimating the impact for the average residential customer, PRISM estimates impacts for three subsets of residential customers based on the presence of central air conditioning (CAC): CAC with no enabling technology (such as a price-sensitive thermostat or direct load control switch), CAC with an enabling technology, and no CAC.

The PRISM Impacts Model consists of four worksheets. The purpose of each worksheet is described below.

1. PRISM Impacts Inputs
All user-defined inputs to the model are entered into the PRISM Impacts Inputs worksheet. In the All-in Rate table, the user enters both the current rate and the dynamic pricing rate that is being analyzed. These rates are entered as all-in rates. In other words, they incorporate generation charges, any other variable charges, and any fixed charges on a $/kWh basis. Default version of the model is set up to accept load shapes for the average residential customer, the average customer with central air conditioning (CAC), and the average customer without CAC for a hypothetical LSE. These could be replaced with other residential customer types. In the CAC Saturation table, the user enters the CAC saturation for the region. In the Weather Data table, the user enters the weather conditions for the region of interest. The weather conditions are based on cooling degree-hours data.

2. Elasticity Estimates
The inputs from the PRISM Impacts Inputs worksheet are used in the Elasticity Estimates worksheet. This worksheet contains the PRISM model coefficients that were estimated from the data obtained during the California Statewide Pricing Pilot (SPP). The model coefficients, when combined with the input parameters, produce elasticity estimates by customer type and day type. These coefficients can be easily replaced with some other coefficients if a utility has estimated its own price responsiveness model or chooses to borrow the coefficients from some other utilities.

3. Impacts-per-Participant
The Impacts per Participant worksheet reads in each customer type's load shape and rate and, using the elasticities calculated in the Elasticity Estimates worksheet, calculates the average kWh-per-hour reduction for each period (i.e., peak period during critical days, off-peak period during non-critical days, etc). This is also represented as the percent reduction in demand during each period.

4. Impact Summary
The Impact Summary worksheet simply summarizes the output that is calculated in the Impacts-per-Participant worksheet. Table A-1 provides an example of the results summary worksheet assuming a critical peak price of $1.30 per kWh, a peak price of $0.14 per kWh, and an off-peak price of $0.083 per kWh. This worksheet provides two impacts: the change in consumption in the peak and off-peak periods by day type in terms of kWh per hour, and percentage change from the original load. These results show that the change in consumption during critical peak hours for the average residential customer is a reduction of 24 percent.

Table A-1 Example Output from PRISM Impact Summary Worksheet

Change in Consumption, by Customer Type (kWh per Hour)

	Residential			
	Average	**CAC**	**No CAC**	**CAC + Tech**
Critical Days - Peak	-0.65	-0.81	-0.20	-1.06
Critical Days - Off-Peak	0.09	0.10	0.05	0.13
Non-Critical Days - Peak	-0.04	-0.05	-0.01	-0.07
Non-Critical Days - Off-Peak	0.04	0.05	0.01	0.07

Change in Consumption, by Customer Type (% of Original Load)

	Residential			
	Average	**CAC**	**No CAC**	**CAC + Tech**
Critical Days - Peak	-24.2%	-28.4%	-10.6%	-36.9%
Critical Days - Off-Peak	4.7%	4.8%	4.0%	6.2%
Non-Critical Days - Peak	-2.6%	-3.1%	-1.3%	-4.0%
Non-Critical Days - Off-Peak	3.1%	3.7%	1.2%	4.9%

2- CES Model Discussion

As mentioned earlier, one of the more popular and theoretically appealing model specifications is the constant elasticity of substitution (CES) demand system. Its application to electricity pricing centers on the substitution equation (1). The equation expresses the peak to off-peak quantity ratio as a function of the peak to off-peak price ratio[42], a weather term representing the difference in cooling degree hours between the peak and off peak periods[43] and fixed effects variable for each customer.

$$\ln\left(\frac{Q_p}{Q_{op}}\right) = \alpha + \sigma \ln\left(\frac{P_p}{P_{op}}\right) + \delta(CDH_p - CDH_{op}) + \sum_{i=1}^{N} \theta_i D_i + \varepsilon \qquad \textbf{(1)}$$

where:

Q_p = average energy use per hour in the peak period for the average day

Q_{op} = average energy use per hour in the off-peak period for the average day

42 It is important to note that this specification can be estimated without any concerns about simultaneous equation bias since prices are set ex ante in just about all of the experiments reviewed in the paper and in a few of the full-scale deployments noted below, the number of participants was not large enough to create demand response of such magnitude that it would influence prices in retail markets.

43 The difference in cooling degree hours per hour between peak and off-peak periods is used rather than the ratio because on some days, there are zero cooling degree hours in the off-peak period and using the ratio would result in division by zero on these days.

σ = the elasticity of substitution between peak and off-peak energy use (following convention, this is taken to be a positive number for substitutes and a negative number for complements)
P_p = average price during the peak pricing period
P_{op} = average price during the off-peak pricing period
δ = measure of weather sensitivity
CDH_p = cooling degree hours per hour during the peak pricing period
CDH_{op} = cooling degree hours per hour during the off-peak pricing period
θ_i = fixed effect coefficient for customer i
D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are a total of N customers.
ε = random error term

Equation (2) expresses daily energy use as a function of daily average price, daily cooling degree hours and the fixed effects variables.

$$\ln\left(Q_d\right) = \alpha + \eta_d \ln\left(P_d\right) + \delta(CDH_d) + \sum_{i=1}^{N} \theta_i D_i + \varepsilon \qquad \textbf{(2)}$$

where:

Q_d = average daily energy use per hour
η_d = the price elasticity of demand for daily energy (defined below)
P_d = average daily price (e.g., a usage weighted average of the peak and off-peak prices for the day)
CDH_d = cooling degree hours per hour during the day
ε = regression error term

The two summary measures of price responsiveness in the CES demand system are the elasticity of substitution (σ) and the daily price elasticity of consumption (η).

It is plausible that the elasticity of substitution and/or the daily price elasticity would differ across customers who have different socio-economic characteristics (e.g., different appliance ownership, different income levels, etc.). The elasticity may also vary between hot and cool days. The CES model can be modified to allow the elasticities to vary with weather and socio-economic factors, such as central air conditioning (CAC) ownership. Equation (3) provides an example of the substitution equation that allows price responsiveness to vary with CAC ownership and weather. Equation (4) shows how the elasticity of substitution would be calculated from this model specification. Equations (5) and (6) show the demand models for daily energy use and the corresponding equation for the daily price elasticity as a function of weather and CAC ownership.

$$\ln\left(\frac{Q_p}{Q_{op}}\right) = \alpha + \sum_{i=1}^{N}\theta_i D_i + \sigma \ln\left(\frac{P_p}{P_{op}}\right) + \delta(CDH_p - CDH_{op}) + \lambda(CDH_p - CDH_{op})\ln\left(\frac{P_p}{P_{op}}\right) + \phi(CAC)\ln\left(\frac{P_p}{P_{op}}\right) + \varepsilon \quad \textbf{(3)}$$

The elasticity of substitution (ES) in this model is a function of three terms, as shown below:

$$\text{ES}=\sigma + \lambda(CDH_p - CDH_{op}) + \phi(CAC) \quad \textbf{(4)}$$

Other customer characteristics, such as income, household size, and number of people in the household, may also influence the elasticities in the CES model. They can be included in the specification by introducing additional price interaction terms in a similar manner to the CAC and weather terms shown above.

$$\ln(Q_D) = \alpha + \sum_{i=1}^{N}\theta_i D_i + \eta\ln(P_D) + \rho(CDH_D) + \chi(CDH_D)\ln(P_D) + \xi(CAC)\ln(P_D) + \varepsilon \quad \textbf{(5)}$$

where:

Q_D = average daily energy use per hour
η = the daily price elasticity
P_D = average daily price
ρ = measure of weather sensitivity
χ = the change in daily price elasticity due to weather sensitivity
CDH_D = average daily cooling degree hours per hour (base 72 degrees)
ξ = the change in daily price elasticity due to the presence of central air conditioning
CAC = 1 if a household owns a central air conditioner, 0 otherwise
θ_i = fixed effect for customer i
D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are a total of N customers.
ε = error term.

The composite daily price elasticity in this model is a function of three terms, as shown below:

$$\text{Daily}=\eta + \chi(CDH_D) + \xi(CAC) \quad (6)$$

BIBLIOGRAPHY

Aubin, Christophe, Denis Fougere, Emmanuel Husson and Marc Ivaldi (1995). "Real-Time Pricing of Electricity for Residential Customers: Econometric Analysis of an Experiment," *Journal of Applied Econometrics*, 10, S171-191.

Bandt, William D., Tom Campbell, Carl Danner, Harold Demsetz, Ahmad Faruqui, Paul R. Kleindorfer, Robert Z. Lawrence, David Levine, Phil McLeod, Robert Michaels, Shmuel S. Oren, Jim Ratliff, John G. Riley, Richard Rumelt, Vernon L. Smith, Pablo Spiller, James Sweeney, David Teece, Philip Verleger, Mitch Wilk, and Oliver Williamson (2003). "2003 Manifesto on the California Electricity Crisis." The manifesto can be accessed at this web site: http://www.aei-brookings.org/publications/abstract.php?pid=341. May 2003.

Borenstein, Severin (2002). "The Trouble with Electricity Markets: Understanding California's Restructuring Disaster," *Journal of Economic Perspectives*, 16:1, 191-211, Winter.

Borenstein, Severin, Michael Jaske, and Arthur Rosenfeld (2002). "Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets." Center for the Study of Electricity Markets, Paper CSEMWP 105, October 31.

Borenstein, Severin (2005). "The Long-run Efficiency of Real-Time Pricing," *The Energy Journal*, 26:3, 93-116,

Braithwait, S. D. (2000). "Residential TOU Price Response in the Presence of Interactive Communication Equipment." In Faruqui and Eakin (2000).

California Energy Commission (2008). "Proposed Load Management Standards," Draft Committee Report, November, CEC-400-2008-027-CTD.

Caves, D. W., L. R. Christensen, and J. A. Herriges (1984). "Consistency of Residential Customer Response in Time-of-Use Electricity Pricing Experiments." *Journal of Econometrics* 26:179-203.

Chao, Hung-po (1983). "Peak-Load Pricing and Capacity Planning with Demand and Supply Uncertainty," *Bell Journal of Economics* 14:1, 170-90, Spring.

Chao, Hung-po and Robert Wilson (1987). "Priority Service: Pricing, Investment and Market Organization," *American Economic Review* 77:5, 899-916.

Charles River Associates (2005). "Impact Evaluation of the California Statewide Pricing Pilot." March 16. The report can be downloaded from: http://www.calmac.org/publications/2005-03-24_SPP_FINAL_REP.pdf.

Colebourn H. (2006). "Network Price Reform." presented at BCSE Energy Infrastructure& Sustainability Conference. December.

Crew, Michael A., Chitru S. Fernando and Paul R. Kleindorfer (1995). "The Theory of Peak Load Pricing: A Survey," *Journal of Regulatory Economics*, 8:215-248.

Energy Insights Inc. (2008a). "Xcel Energy TOU Pilot Final Impact Report." March.

Energy Insights Inc. (2008b). "Experimental Residential Price Response Pilot Program March 2008 Update to the 2007 Final Report." March.

Faruqui, Ahmad, Ryan Hledik, Sanem Sergici. 2009. "Piloting the Smart Grid." *The Electricity Journal*, Vol. 22, Issue 7: 55-69.

Faruqui, Ahmad and Lisa Wood. 2008. "Quantifying the Benefits of Dynamic Pricing in the Mass Market. Prepared for the Edison Electric Institute.

Faruqui, Ahmad (2007). "Breaking out of the bubble: using demand response to mitigate rate shock," 46-51, *Public Utilities Fortnightly*, March.

Faruqui, Ahmad, Robert Earle. 2006. "Toward a New Paradigm for Valuing Demand Response." *The Electricity Journal,* Vol. 19, Issue 7: 21-31.

Faruqui, Ahmad, Hung-po Chao, Victor Niemeyer, Jeremy Platt and Karl Stahlkopf (2001a). "Analyzing California's power crisis," *The Energy Journal*, Vol. 22, No. 4, 29-52.

Faruqui, Ahmad, Hung-po Chao, Victor Niemeyer, Jeremy Platt and Karl Stahlkopf (2001b). "Getting out of the dark," *Regulation*, Fall, 58-62.

Faruqui, Ahmad and B. Kelly Eakin. 2002. *Electricity Pricing in Transition*, Kluwer Academic Publishers, 2002.

Faruqui, Ahmad and B. Kelly Eakin. 2000. *Pricing in Competitive Electricity Markets*, Kluwer Academic Publishers.

Faruqui, Ahmad and Stephen S. George. 2002. "The Value of Dynamic Pricing in Mass Markets." *The Electricity Journal* 15:6, 45-55.

Faruqui, Ahmad and Stephen S. George. 2003. "Demise of PSE's TOU Program Imparts Lessons." *Electric Light & Power* Vol. 81.01:14-15.

Faruqui, Ahmad and Stephen S. George. 2005. "Quantifying Customer Response to Dynamic Pricing," *The Electricity Journal*, May.

Faruqui, Ahmad, Ryan Hledik, Samuel Newell, and Johannes Pfeifenberger. 2007. "The Power of Five Percent." *The Electricity Journal* Vol. 20, Issue 8:68-77.

Faruqui, Ahmad and J. Robert Malko. 1983. "The Residential Demand for Electricity by Time-of-Use: A Survey of Twelve Experiments with Peak Load Pricing." *Energy* Vol. 8:10. 781-795.

Federal Energy Regulatory Commission. 2009. A National Assessment of Demand Response Potential. Staff Report. Washington, D.C.

Federal Energy Regulatory Commission. 2008. Assessment of Demand Response and Advanced Metering. Staff Report. Washington, D. C.

Filippini, Massimo. 1995. "Swiss Residential Demand for Electricity by Time-of-Use: An Application of the Almost Ideal Demand System," *Energy Journal*, 16:1, 27-39.

Giraud, Denise. 2004. "The tempo tariff," Efflocon Workshop, June 10. http://www.efflocom.com/pdf/EDF.pdf.

Giraud, Denise and Christophe Aubin. 1994. "A New Real-Time Tariff for Residential Customers," in Proceedings: 1994 Innovative Electricity Pricing Conference, EPRI TR-103629, February.

Herter, Karen. 2007. "Residential implementation of critical-peak pricing of electricity," *Energy Policy*, 35:4, April, 2121-2130.

Herter, Karen, Patrick McAuliffe and Arthur Rosenfeld. 2007. "An exploratory analysis of California residential customer response to critical peak pricing of electricity," *Energy*, 32:1, January, 25-34.

Idaho Power Company. 2006. "Analysis of the Residential Time-of-Day and Energy Watch Pilot Programs: Final Report." December.

Kiesling, Lynne (2008). "Digital Technology, Demand Response, and Customer Choice: Efficiency Benefits," NARUC Winter Meetings, Washington, DC, February 18.

Levy, Roger, Ralph Abbott and Stephen Hadden (2002). *New Principles for Demand Response Planning*. EPRI EP-P6035/C3047, March.

Littlechild, Stephen C. (2003). "Wholesale Spot Price Pass-Through," *Journal of Regulatory Economics*, 23:1, January. 61-91.

Matsukawa, Isamu. 2001. "Household Response to Optional Peak-Load Pricing of Electricity," *Journal of Regulatory Economics*. 20:3, 249-261.

Morgan, Rick (2009). "Rethinking dumb rates," *The Public Utilities Fortnightly*, March.

Ontario Energy Board. 2007. "Ontario Energy Board Smart Price Pilot Final Report." Toronto, Ontario, July.

Pacific Northwest National Laboratory. 2007. "Pacific Northwest GridWise Testbed Demonstration Projects Part 1: Olympic Peninsula Project." Richland, Washington. October.

Pfannenstiel, Jackie and Ahmad Faruqui (2008). "Mandating Demand Response," *The Public Utilities Fortnightly*, January.

PSE&G and Summit Blue Consulting (2007). "Final Report for the Mypower Pricing Segments Evaluation." Newark, New Jersey. December.

Reiss, Peter C. and Matthew W. White (2008). "What changes energy consumption? Prices and public pressures," *The Rand Journal of Economics*, Vol. 39, No. 3, Autumn, 636-663.

RLW Analytics (2004). "AmerenUE Residential TOU Pilot Study Load Research Analysis: First Look Results." February.

Rocky Mountain Institute (2006). "Automated Demand Response System Pilot: Final Report." Snowmass, Colorado. March.

Shadish, William R., Thomas D. Cook and Donald T. Campbell (2002). Experimental and Quasi-Experimental Designs for Generalized Causal Inference, Houghton Mifflin Company, Boston and New York.

Summit Blue Consulting, LLC. (2006). "Evaluation of the 2005 Energy-Smart Pricing Plan-Final Report." Boulder, Colorado. August.

Summit Blue Consulting, LLC. (2007). "Evaluation of the 2006 Energy-Smart Pricing Plan-Final Report." Boulder, Colorado.

Taylor, Thomas N., Peter M. Schwarz and James E. Cochell (2005). "24/7 Hourly Response to Electricity Real-Time Pricing with up to Eight Summers of Experience," *Journal of Regulatory Economics*, 27:3, 235-262.

U.S. Demand Response Coordinating Committee (2008). "Demand Response and Smart Metering Policy Actions Since the Energy Policy Act of 2005: A Summary for State Officials," The National Council on Electricity Policy, Fall.

U.S. Department of Energy (2006). "Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them: A Report to the United States Congress Pursuant to Section 1252 of the Energy Policy Act of 2005." February.

Vickrey, W. S. (1971). "Responsive Pricing of Public Utility Services," *Bell Journal of Economics*, 2:1, 337-46, Spring.

Voytas, Rick (2006). "AmerenUE Critical Peak Pricing Pilot." presented at U.S. Demand Response Research Center Conference, Berkeley, California, June.

Wellinghoff, Jon and David M. Morenoff (2007). "Recognizing the importance of demand response: The second half of the wholesale electric market equation," *Energy Law Journal*, Volume 28, No. 2.

Wolak, Frank A. (2006). "Residential Customer Response to Real-Time Pricing: The Anaheim Critical-Peak Pricing Experiment." Available from http://www.stanford.edu/~wolak.

Wolak, Frank A. (2007). "Managing Demand-Side Economic and Political Constraints on Electricity Industry Re-structuring Processes." Available from http://www.stanford.edu/~wolak.