The Arc of Price Responsiveness – Consistency of Results across Time-Varying Pricing Studies

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ABSTRACT

This paper conducts a meta-analysis of 151 pricing treatments that were offered on an experimental or full-scale basis in seven countries located in four continents. It draws upon *The Brattle Group's* Arcturus database which contains information on specific rate designs, whether or not enabling technologies were offered to customers in addition to these time-varying rates, and the amount of peak reduction resulting from each of the price and price-technology treatments. A useful way to measure the intensity of the price signal is through the peak-to-off-peak price ratio. A logarithmic model is used to quantify the relationship between the price ratio and the amount of peak reduction. When demand response is expressed as a function of the price ratio, a clear pattern begins to emerge. Customers respond to rising prices by lowering their peak demand, and as the price continues to increase, they continue to increase their response, but at a decreasing rate. In addition, the use of enabling technologies boosts the amount of demand response. This yields two "arcs" of price responsiveness. Overall, we find a significant amount of consistency in the experimental results. This finding is consistent with earlier analysis with time-of-use pricing studies that took place under Department of Energy (DOE) sponsorship in the late 1970s and early 1980s. The results of this paper support the case for the rollout of dynamic pricing and can serve as a tool to quantify the potential peak reductions that result from different time-varying rates.

Introduction

Through the use of time-varying rates, utilities can lower their cost of doing business by lowering peak loads and raising load factors. Rising costs have become a major concern for utilities. Many are deploying advanced metering infrastructure (AMI) to improve the economics of the distribution system. AMI is a prerequisite for dynamic pricing. About one of four households is on AMI today. However, according to the latest FERC survey, less than two percent of households are on any form of time-varying rate and most of these are on simple, non-dynamic time-of-use rates. Over the past decade, a number of dynamic pricing and time-of-use studies have been conducted around the globe. Some of these have been randomized experiments, some have been quasi experiments, some have been demonstrations, and some have been full-scale deployments. A full-blown meta-analysis would require the analyst to normalize for differences in experimental design; it would also require access to individual customer data. Such a study was carried out by EPRI in the early 1980s by using data from five experiments with time-of-use pricing (D.W. Caves *et. al.*1984). Lack of individual customer data prevents us from carrying out such an analysis at this time. However, as a first step in that direction, we have assembled aggregate data on demand response and prices from 33 studies which have published their findings. These studies encompass experiments, quasi experiments and full-scale deployments.

We have compiled the information from these studies in a database called Arcturus. The 33 studies encompass a total of 151 treatments (where a treatment is defined as a unique combination of some type of time-varying pricing design and enabling technology). At first glance, there is little consistency in the results: the amount of demand response exhibited across the 151 treatments ranges from zero percent to 58 percent. This wide range of impacts has led some policy makers to conclude that our understanding of customer behavior is not strong enough to proceed with universal deployment of dynamic pricing and time-of-use pricing, even though smart meters are being deployed. However, this range just represents the raw data, unfiltered by the intensity of the price signal that was conveyed to participants. If the data from those treatments that only featured time-varying prices are plotted separately from those that featured time-varying prices with enabling technology, even sharper results are obtained, as enabling technologies increase demand response even more.

We examine the impact of the price ratio on the magnitude of the reduction in peak demand using a simple regression model. Because the amount of demand response varies with the presence or absence of enabling technology, such as a smart thermostat, an energy orb or an in-home display, we include a variable that indicates the use of enabling technologies. We find a statistically significant relationship between the price ratio and the amount of peak reduction; the interaction variable between price and the use of enabling technologies has a significant relationship with the amount of peak reduction as well. This relationship is termed the Arc of Price Responsiveness for reasons that will become clear later in this paper. We find that for a given price ratio, experiments with enabling technologies tend to produce larger peak reductions, and display more price-responsiveness.

The Time-Varying Rate Designs

Time-varying rate designs charge different electricity rates at different times of the day and year. These rates reflect the time-varying cost of supplying electricity and incentivize consumers to decrease their electrical usage during peak hours and/or shift consumption to less expensive off-peak hours. This paper examines the resulting peak demand reductions from four types of time-varying rates: Time-Of Use (TOU), Critical Peak Pricing (CPP), Peak Time Rebate (PTR), and Variable Peak Pricing (VPP) rates. The last three options fall under the rubric of dynamic pricing. While Real-Time Pricing (RTP) rates also fall into that rubric, and have been offered to customers in some of the published studies, the lack of a clear price ratio inhibits us from using these treatments in this paper.

A **time-of-use (TOU)** rate could either be a time-of-day rate, in which the day is divided into time periods with varying rates, or a seasonal rate into which the year is divided into multiple seasons and different rates provided for different seasons. TOU rates are fixed by period and consequently offer certainty as to what the rate will be and when they will occur. In a time-of-day rate, a peak period might be defined as the period from 12 pm to 6 pm on weekdays, with the remaining hours being off-peak. The price would be higher during the peak period and lower during the off-peak period, mirroring the variation in marginal costs by pricing period. TOU rates with three periods have also been offered. Such rate schemes include a shoulder (or mid-peak) period, where the cost of electricity is lower than peak period rates, but higher than off-peak period rates. Additionally, TOU rates may future two peak periods (such as a morning peak from 8 am to 10 am, and an afternoon peak from 2 pm to 6 pm).

On a **critical peak price (CPP)** rate, customers pay higher peak period prices during the few days a year when wholesale prices are the highest (typically the top 10 to 15 days of the year which account for 10 to 20 percent of system peak load). This higher peak price reflects both energy and capacity costs and, as a result of being spread over relatively few hours of the year, can be in excess of $1 per kWh. In return, the customers pay a discounted off-peak price that more accurately reflects lower off-peak energy supply costs for the duration of the season (or year). Customers are typically notified of an upcoming “critical peak event” one day in advance, but if enabling technologies are used, these rates can also be activated on a day-of basis.

Like on a CPP rate, customers on **variable peak price (VPP)** rates pay higher peak period prices during a few days a year when wholesale prices are highest. The main difference between a critical peak price and a variable peak price is that the variable peak price varies from one event day to the next, as determined by market rates. On-peak prices generally vary each day based on day-ahead market prices. On non-event days, the VPP rate acts like a normal TOU rate, with fixed period prices.

If a CPP tariff cannot be rolled out because of political or regulatory constraints, some parties have suggested the deployment of a **peak-time rebate (PTR)**. Instead of charging a higher rate during critical events, participants are paid for load reductions (estimated relative to a forecast of what the customer otherwise would have consumed). If customers do not wish to participate, they simply buy electricity through at the existing rate. There is no rate discount during non-event hours.

Participants in **real-time pricing (RTP)** programs pay for energy at a rate that is linked to the hourly market price for electricity. Depending on their size, participants are typically made aware of the hourly prices on either a day-ahead or hour-ahead basis. Typically, only the largest customers —above one megawatt of load — face hour-ahead prices. These programs post prices that most accurately reflect the cost of producing electricity during each hour of the day, and thus provide the best price signals to customers, giving them the incentive to reduce consumption at the most expensive times.

Enabling technologies such as programmable thermostats and in-home displays (IHDs) can be offered with time-varying rates in order to enhance the effectiveness of the rates by automating response and minimizing customer transaction costs. Programmable communicating thermostats (PCTs) can receive a signal during a critical peak pricing event and automatically reduce air-conditioning usage to a level that is specified by the customer, reducing the need to manually respond to high-priced events. Information-enhancing technologies such as in-home displays (IHDs) can give customer information such as the amount of electricity that they are using, what it is costing them, how that translates into their carbon footprint, how close they are to energy savings goals, and other such data. The information can also be provided online through web portals or even through a smartphone. Energy orbs provide visual feedback to customers by changing color depending on the price of electricity.

The 33 Studies

The 33 studies encompassing 151 experimental treatments in the Arcturus database span four continents and seven countries.

sorts the peak reductions for each of the 151 experimental treatments from lowest to highest. At first glance, there is little consistency in the results, for demand response varies from 0 percent to 58 percent. Some of the variation in demand response can be attributed to the different rate types tested. Grouping the results by rate type slightly improves the resolution, but not by much. There still remains significant variation among pricing types, as shown in Figure 1. Impacts from Residential Time-Varying Pricing Tests, Sorted from Lowest to Highest

. Due to their tendency to have higher price ratios than TOU rates, we find that CPP and PTR rates tend to result in higher customer response.[1] We hypothesize that this is primarily due to the use of high price ratios for these rates. By filtering by rate type and the use of enabling technologies, as done in Figure 2. Impacts from Pricing Tests, by Rate Type

[1] For the PTR rate, the effective critical peak price is calculated by adding the peak time rebate to the rate the customer normally pays during that time period (in the absence of the rebate).

, we can see a clearer picture emerge from the data. The use of enabling technology appears to increase demand response to levels above pricing-only observations at the same price ratio.

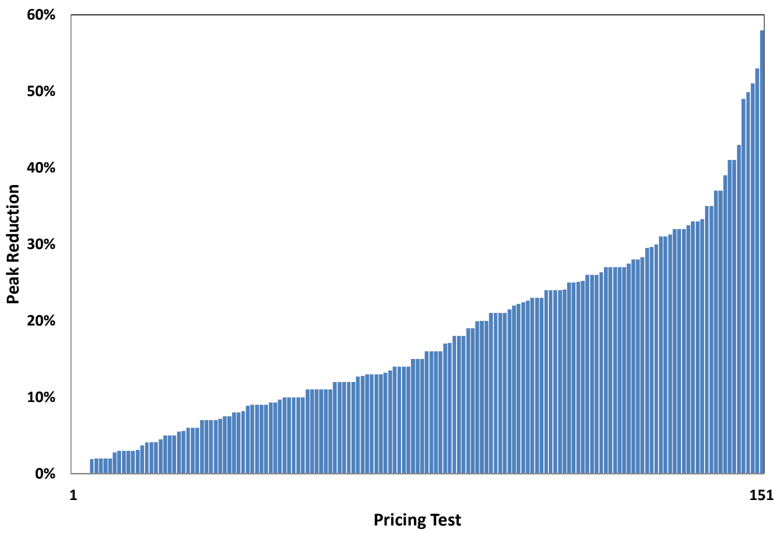


Figure 1. Impacts from Residential Time-Varying Pricing Tests, Sorted from Lowest to Highest

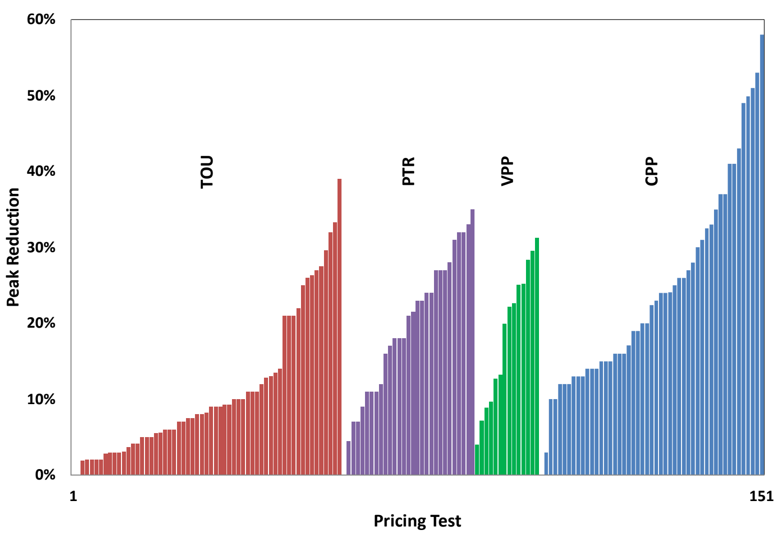


Figure 2. Impacts from Pricing Tests, by Rate Type

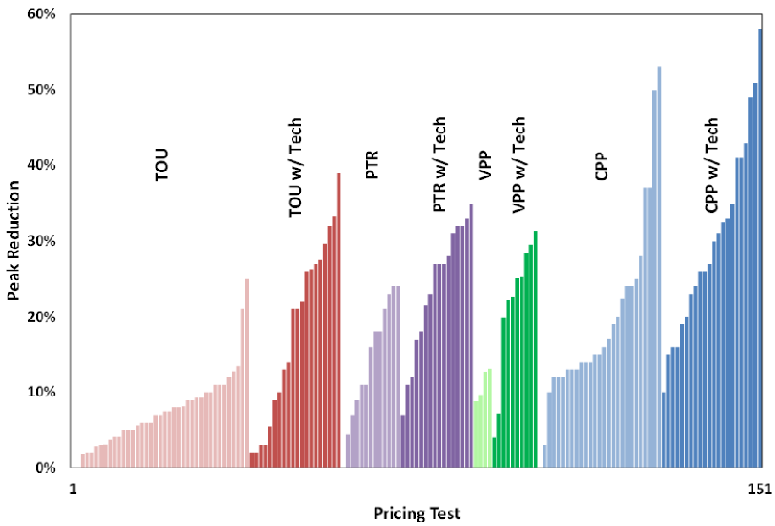


Figure 3. Impacts from Pricing Tests by Rate Type and Use of Enabling Technologies

Even after sorting the observations by rate type and the use of enabling technology, significant unexplained variation remains. As hypothesized before, the range of results may be due to the variation in the peak-to-off-peak price ratio employed across the studies. In order to examine this, we start by carrying out an exploratory data analysis by plotting demand response as a function of the price ratio. The plots initially focus only on pricing treatments that were not accompanied by enabling technology. These are then followed by plots that focus on pricing treatments that were also technology enabled. As seen below in Figure 4, the 83 price-only treatments fall into a tight pattern.

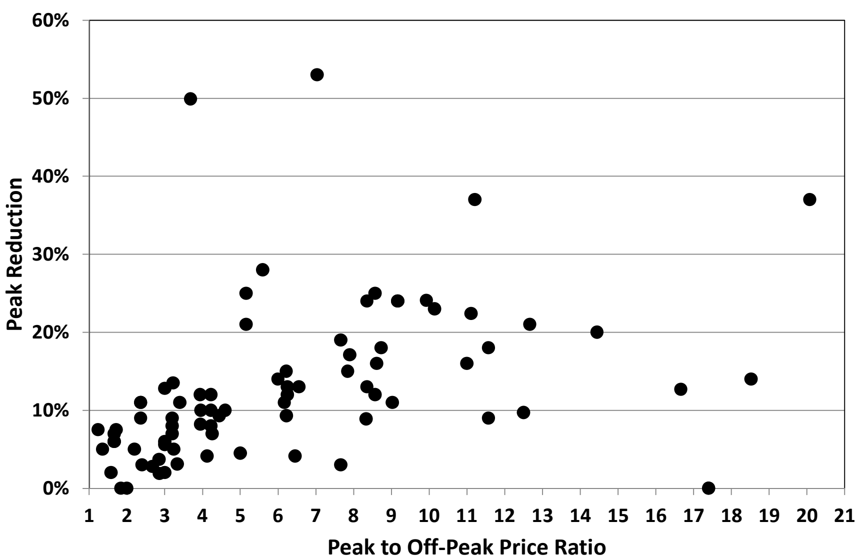


Figure 4. Price-Only Treatments[2]

The 68 treatments involving price and enabling technologies have a more diffuse pattern, but peak reductions still tend to increase with the peak-to-off-peak price ratio. In addition, for a given price ratio, peak reductions for these technology enabled projects tend to be greater than exhibited by price-only treatments.

[2] Data points from the Japan and PSE&G pricing studies are omitted because of extremely high price ratios.

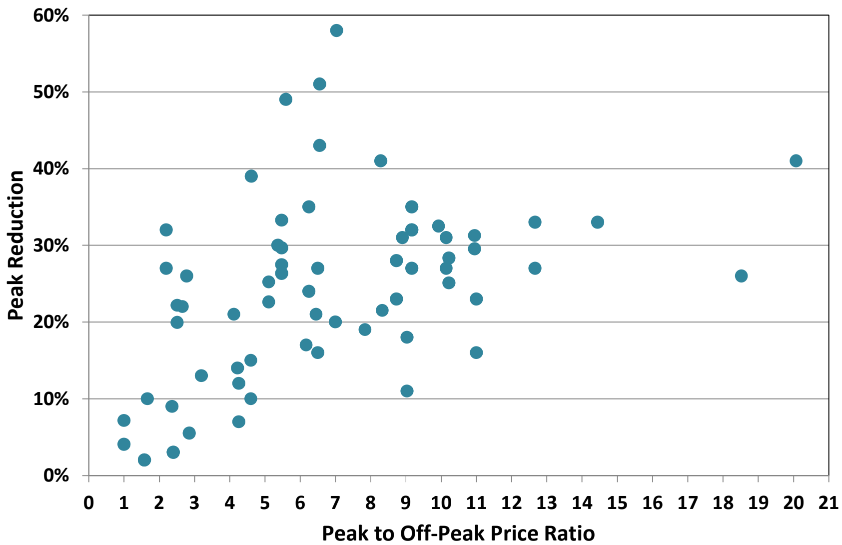


Figure 5. Price + Enabling Technology Treatments[3]

Methodology

For each experimental treatment in the Arcturus database, we plot the all-in peak-to-off-peak price ratio against the corresponding peak reduction. The exploratory data analysis leads us to estimate a simple regression model for the 151 experimental treatments that examines the effect of the price ratio and use of enabling technology on demand response. Using a logarithmic specification, we model the amount of demand response, expressed as a percentage, as a function of the price ratio, with and without enabling technology.

Logarithmic Model

$$y = a + b*\ln(\textit{price ratio}) + c*\ln(\textit{price ratio*tech})$$

Where y = *peak demand reduction percent*

In the above equation, "*tech*" is a binary variable which acquires a value of one when enabling technology is offered in conjunction with price. The most common types of enabling technologies offered with the pricing rates in our database are smart thermostats, in-home displays (IHDs), and energy orbs.

Results

When we fit the logarithmic model to the dataset of 151 observations, we estimate a coefficient of 0.046 for the natural log of the price ratio and 0.058 for the natural log of the price ratio*tech variable. Both variables are significant at the 0.001 level. The results reveal that as the peak-to-off-peak price ratio increases, the peak reduction also increases. In addition, the positive and significant relationship between peak reduction and the price*tech variable signifies that the use of enabling technology further boosts demand response. The R squared value of 0.038 means that approximately 38% of the variation in the dependent variable (i.e. peak demand reduction) can be explained by the independent variables (i.e. the price ratio and price ratio*tech variables).

Table 1. Regression Results

[3] One data point from PSE&G is omitted because of its extremely high price ratio.

Coefficient	Regression
Ln(Price Ratio)	0.046 ***
	0.012
Ln(Ratio_EnablingTech)	0.058 ***
	0.008
Intercept	0.054
	0.020
Adjusted R-Squared	0.380
F-Statistic	46.89
Observations	151
Standard errors are shown below the estimates	
*** $p \leq 0.001$	
** $p \leq 0.01$	
* $p \leq 0.05$	

The analysis yields two "arcs of price responsiveness" for pricing-only treatments and price-tech treatments. These Arcs of Price Responsiveness can be used to make preliminary assessments about expected customer impacts from various time-varying rates. For example, for a peak-to-off-peak price ratio of 5:1, the expected peak reductions for price-only and price-technology treatments are ~12.8% and ~22.1% respectively. For a price ratio of 10:1, these reductions would increase to ~15.9% and ~29.3% respectively.

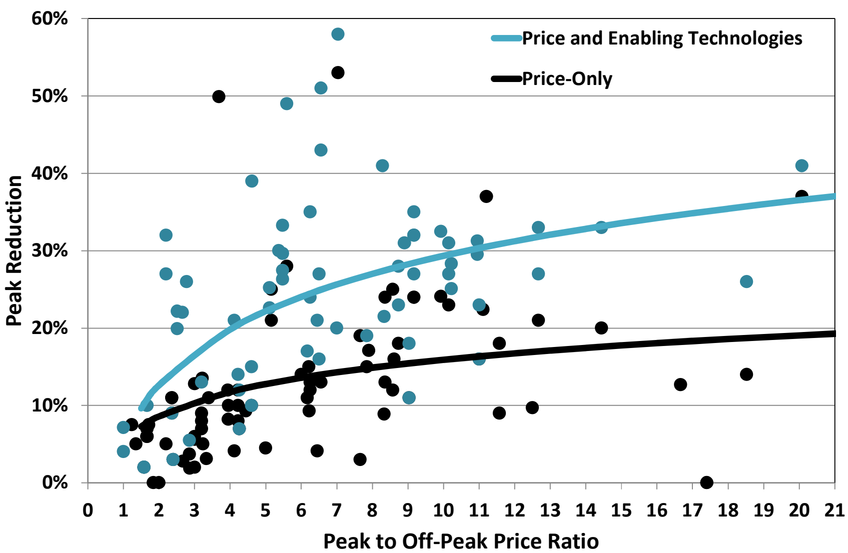


Figure 6. Arc of Price Responsiveness

The graphical analysis in Figure 6 shows some of the 151 treatments yield either extremely high or extremely low impacts. We have categorized treatments with extremely high impacts (~40% for pricing-only treatments and ~50% for price-tech treatments) or extremely low impacts (~0%) as outliers. There are a total of 12 outliers in the dataset.

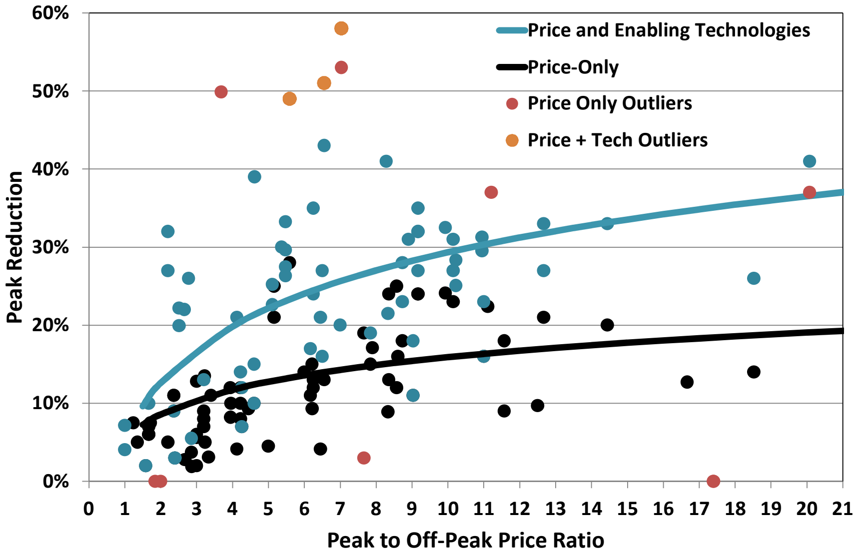
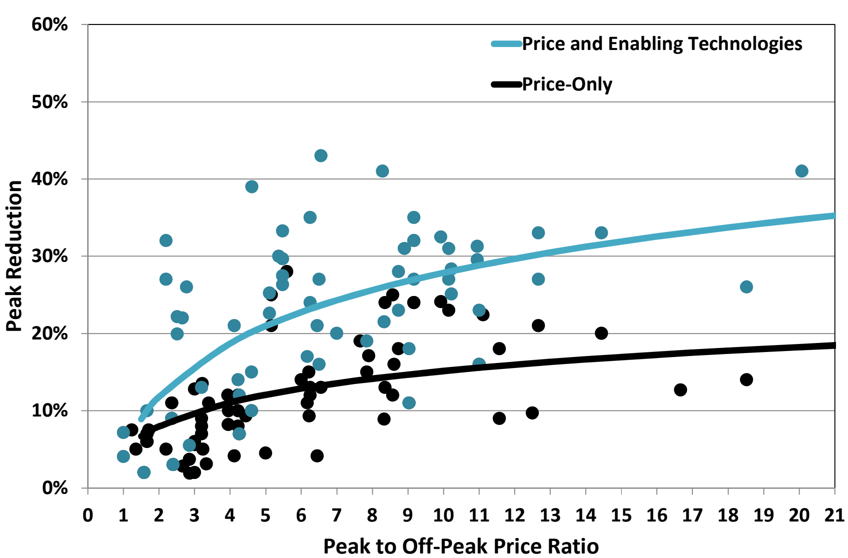


Figure 7. Flagging the Outliers

When we drop the outliers from the dataset and re-estimate our logarithmic model, the results improve. Most notably, the Adjusted R-Squared value increases from 0.380 to 0.533. Therefore, over half of the variation in peak demand reductions can be explained by the price ratio and use of enabling technologies. We estimate a coefficient of 0.045 for the natural log of the price ratio and 0.055 for the natural log of the price ratio*tech variable. Both variables are significant at the 0.001 level. Additionally, the standard errors for these variables are lower than before.

As done earlier, the Arcs of Price Responsiveness (shown in Figure 8) can be used to make preliminary assessments about expected demand response from time-varying rates. For a price ratio of 5:1, the expected peak reduction in price-only and price-tech experimental treatments is ~12.0% and ~20.9% respectively. For a price ratio of 10:1, expected peak period reductions are ~15.1% and ~27.9% respectively.[4] The preliminary results with the 5:1 price ratio are very similar to the results from the California Statewide Pricing Pilot (SPP) in 2005; this study featured a CPP rate with a price ratio of 6.56 and resulted in a 13% peak reduction (Charles River Associates 2005).



[4] By dropping the outliers from our dataset, our re-estimated arcs predict impacts that are lower than before.

Figure 8. Arc of Price Responsiveness (Excluding Outliers)

Table 2. Regression Results after dropping Outliers

Coefficient	Regression
Ln(Price Ratio)	0.045 ***
	0.009
Ln(Ratio_EnablingTech)	0.055 ***
	0.006
Intercept	0.049
	0.015
Adjusted R-Squared	0.533
F-Statistic	79.62
Observations	139

Standard errors are shown below the estimates
*** $p \leq 0.001$
** $p \leq 0.01$
* $p \leq 0.05$

Comparison to Earlier Meta-Analysis of TOU Experiments

It is useful to put the results of our analysis in historical perspective. We have done this by comparing them to an earlier meta-analysis of TOU pricing experiments. This was carried out in the early 1980s by EPRI and managed by Ahmad Faruqui. In this meta-analysis, data from the five best residential TOU experiments was combined and analyzed. The research team of Douglas Caves and Lau Christensen estimated a CES model. This yielded a variety of elasticities of substitution, one for the average household across all five experiments, an elasticity for households with all major electric appliances living in a hot climate, and an elasticity for households with no major electric appliances in a cool climate (D.W. Caves *et. al.*1984). The elasticity of substitution for this meta-analysis captures a customer's decision to shift usage from higher priced peak periods to lower priced off-peak periods. In this instance, negative elasticities of substitution mean that customers will reduce peak period consumption in response to an increase in the price ratio.

Using *Brattle*'s Price Impact Simulation Model (PRISM), which grew out of California's Statewide Pricing Pilot, we have used these elasticities to simulate the impact of different price ratios on peak demand (Faruqui *et. al.* 2006). The results are shown in Figure 9 below.

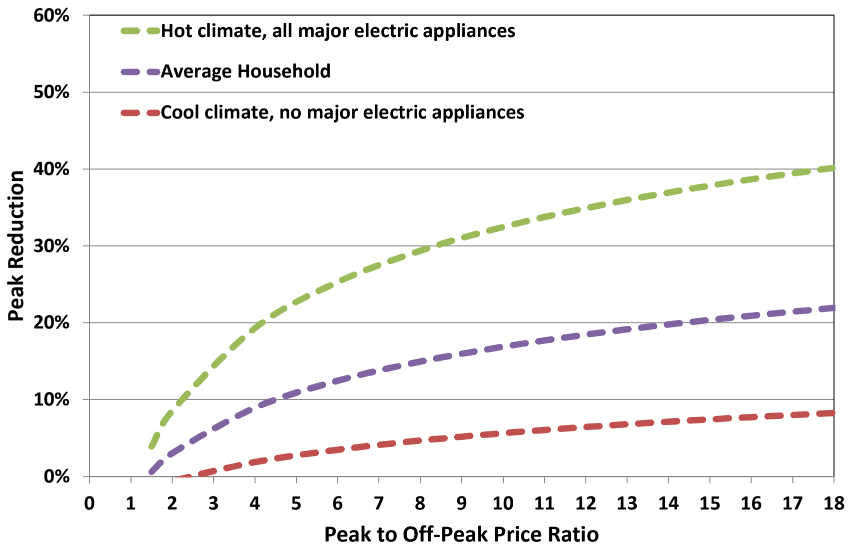


Figure 9. Meta-Analysis of 5 TOU Experiments

And to put these results in perspective, the next figure shows our new Arc of Price Responsiveness for pricing-only treatments superimposed on the previous figure. The results are strikingly similar between the average household results from the early 1980s and the price-only result from the recent studies.

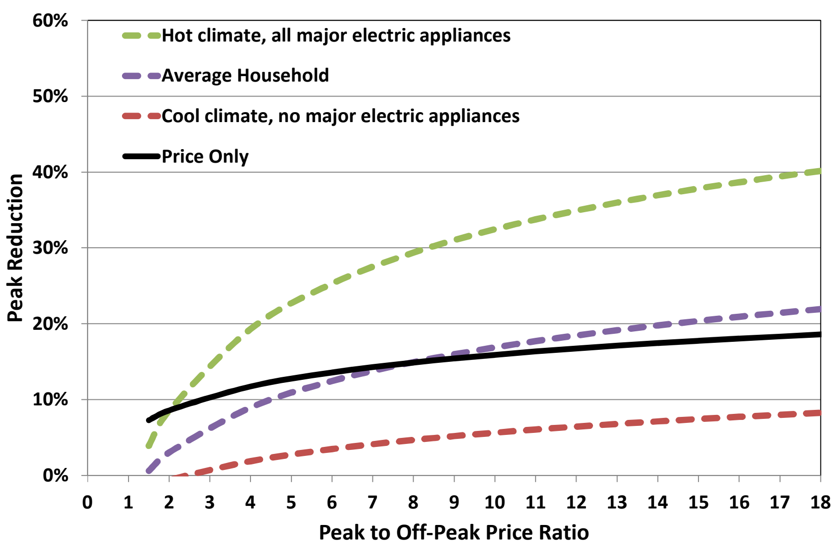


Figure 10. Price-Only Arc Superimposed

Conclusion

The amount of demand response increases as the peak to off-peak price ratio increases but at a diminishing rate. When coupled with enabling technologies, price responsiveness increases even more. Of course, there are many drivers of demand response besides the price ratio. The length of the peak period, number of pricing periods, climate, and appliance ownership can all affect the average customer response during the peak period. Additionally, the marketing of dynamic pricing rates has a tremendous impact on customer response, for customer awareness and education is critical to the success of time-varying pricing. Finally, the section of customers into time-varying rate experiments can affect the results of these studies. Because we were unable to control for these factors in this initial analysis, there are some outliers in our dataset which require further inspection. Even then, the surprising amount of consistency in the results shows that utilities and policymakers can be confident that dynamic pricing and time-of-use pricing will yield significant load reductions.

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Appendix

Summary Statistics on 33 Time-Varying Pricing Studies

No.	Experiment	Location	Year	Rates	Enabling Technologies	Number of Treatments	Season	Full Scale Rollout	Smart Grid Investment Grant (SGIG) Project
1	Ameren Missouri	Missouri	2004, 2005	CPP	CPP w/Tech	4	Summer	No	No
2	Anaheim Public Utilities (APU)	California	2005	CPP	Not tested	1	Summer	No	No
3	Automated Demand Response System (ADRS)	California	2004, 2005	TOU, CPP	TOU w/ Tech, VPP w/ tech	4	Summer	No	No
4	Baltimore Gas & Electric (BGE)*	Maryland	2008, 2009, 2010, 2011	CPP, PTR	CPP w/ Tech, PTR w/ Tech	19	Summer	No	Yes
5	BC Hydro	Ontario, Canada	2008	TOU, CPP	Not tested	8	Winter	No	No
6	California Statewide Pricing Pilot (SPP--Pacific Gas & Electric, San Diego Gas & Electric, Southern California Edison)*	California	2003, 2004	TOU, CPP	CPP w/ Tech	4	Summer	No	No
7	Commonwealth Edison (ComEd)	Illinois	2010	TOU, CPP, PTR	Not tested	3	Summer	No	No
8	Connecticut Light & Power (CL&P)*	Connecticut	2009	TOU, CPP, PTR	TOU w/ Tech, CPP w/ Tech, PTR w/ Tech	18	Summer	No	No
9	Consumers Energy*	Michigan	2010	CPP, PTR	CPP w/ Tech	3	Summer	No	No
10	Country Energy	Australia	2005	CPP	CPP w/ Tech	1	All	No	No
11	GPU	New Jersey	1997	TOU	TOU w/ Tech	2	Summer	No	No
12	Gulf Power	Florida	2000	TOU, CPP	TOU w/ Tech, CPP w/ Tech	2	Summer	No	No
13	Hydro One	Ontario, Canada	2007	TOU	TOU w/ Tech	2	Summer	No	No
14	Hydro Ottawa	Canada	2006	TOU, CPP, PTR	Not tested	6	Summer	No	No
15	Idaho Power	Idaho	2006	TOU, CPP	Not tested	2	Summer	No	No
16	Integral Energy	Australia	2007, 2008	CPP	CPP w/ Tech	2	All	No	No
17	Irish Utilities**	Ireland	2010	TOU	TOU w/ Tech	16	All	No	No
18	Istad Nett AS	Norway	2006	TOU	Not tested	1	Winter	No	No
19	Marblehead Municipal Light Department	Massachussets	2011	CPP	Not tested	1	Summer	No	Yes
20	Mercury Energy	New Zealand	2008	TOU	Not tested	3	Winter	No	No
21	Newmarket Hydro	Ontario, Canada	2007	TOU, CPP	CPP w/ Tech	2	All	No	No
22	Newmarket Tay Power Distribution	Ontario, Canada	2009	TOU	Not tested	1	All	No	No
23	Oklahoma Gas & Electric (OG&E)	Oklahoma	2010	TOU, VPP	TOU w/ Tech, VPP w/ Tech	14	Summer	No	Yes
24	Olympic Peninsula Project	Washington	2007	CPP	CPP w/ Tech	1	Summer	No	No
25	Pacific Gas & Electric (PG&E)	California	2009, 2010	TOU, CPP	Not tested	4	Summer	Yes	No
26	Pepco DC	District of Columbia	2008, 2009	CPP, PTR	CPP w/ Tech, PTR w/ Tech	4	Summer	No	Yes
27	Public Service Electric and Gas Company (PSE&G)	New Jersey	2006, 2007	TOU, CPP	TOU w/ Tech, CPP w/ Tech	8	Summer	No	No
28	Pudget Sound Energy	Washington	2001	TOU	Not tested	1	All	Yes	No
29	Sacramento Municipal Utility District (SMUD)	California	2011	CPP	CPP w/ Tech	2	Summer	No	Yes
30	Salt River Project	Arizona	2008, 2009	TOU	Not tested	2	Summer	Yes	No
31	San Diego Gas & Electric (SDG&E)	California	2011	PTR	PTR w/ Tech	2	Summer	Yes	No
32	Sioux Valley Energy (SVE)	South Dakota	2011	CPP	Not tested	4	Summer	No	Yes
33	Smart Community Pilot Project in Kitakyushu	Japan	2012	VPP	Not tested	4	Summer	No	No
					Total	**151**			

**The Brattle Group* was involved in the evaluation of this experiment

**Run by the Commission for Energy Regulation (CER)