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The Discovery of Price Responsiveness – A Survey of Experiments involving Dynamic Pricing of Electricity

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Abstract

This paper surveys the results from 126 pricing experiments with dynamic pricing and time-of-use pricing of electricity. These experiments have been carried out across three continents at various times during the past decade. Data from 74 of these experiments are sufficiently complete to allow us to identify the relationship between the strength of the peak to off-peak price ratio and the associated reduction in peak demand or demand response. An "arc of price responsiveness" emerges from our analysis, showing that the amount of demand response rises with the price ratio but at a decreasing rate. We also find that about half of the variation in demand response can be explained by variations in the price ratio. This is a remarkable result, since the experiments vary in many other respects – climate, time period, the length of the peak period, the history of pricing innovation in each area, and the manner in which the dynamic pricing designs were marketed to customers. We also find that enabling technologies such as in-home displays, energy orbs and programmable and communicating thermostats boost the amount of demand response. The results of the paper support the case for widespread rollout of dynamic pricing and time-of-use pricing.

Introduction

Electric utilities, which run a capital-intensive business, could lower their costs of doing business by improving their load factor. Other capital intensive industries, such as airlines, hotels, car rental agencies, sporting arenas, movie theaters routinely practice a technique known as dynamic pricing to improve load factor. In dynamic pricing, prices vary to reflect the changing balance of demand and supply through the day, through the week and through the seasons of the year.

Congestion pricing, a simpler form of dynamic pricing, is used to regulate the flow of cars into central cities. Parking spaces in most central cities are priced on a time-of-day basis and in some cities such as San Francisco the prices are varying dynamically. In California, special lanes on freeways are priced dynamically and the Bay Bridge charges toll on a time-of-use basis.

But it has been difficult for electric utilities to follow these examples. There has always been doubt that electric users can change their usage patterns. To assuage these doubts, in the late 1970s and early 1980s, a dozen electricity pricing experiments were carried out with time-of-use rates in the United

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States.[2] They showed that customers do respond to such rates by lowering peak usage and/or shifting it to less expensive off-peak periods. But smart meters that would charge on a time-of-day basis were expensive in those days and little progress occurred in the ensuring years. Even now, less than one percent of the more than 125 million electric customers in the United States are charged on a time-of-use basis.

However, the California energy crisis of 2000-01 reinvigorated interested in dynamic pricing, not only in that state but globally. Over the past decade, two dozen dynamic pricing studies featuring over one hundred dynamic time-of-use and dynamic pricing designs were carried out across North America, in the European Union and in Australia and New Zealand.[3]

These experiments have yielded a rich body of empirical evidence. We have compiled this into a database, *D-Rex*, which stands for *D*ynamic *R*ate *ex*periments. This contains the following data from each pilot: details of the specific rate designs tested in the pilot, whether or not enabling technologies were offered to customers in addition to the time-varying rates, and the amount of peak reduction that was realized with each price-technology combination. The *D-Rex* results provide an important perspective on the potential magnitude of impacts with different dynamic rate approaches and should inform the public debate about the merits of smart meters and smart pricing. Across the 129 dynamic pricing tests, peak reductions range from near zero values to near 60 percent values. However, it would be misleading to conclude that there is no consistency in customer response.[4]

We focus on nine of the best designed, more recent experiments to examine the impact of the peak to-off peak price ratio on the magnitude of the reduction in peak demand, or demand response. 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 separate those pricing tests without and with enabling technology. We find a statistically significant relationship between the price ratio and the amount of peak reduction, and quantify this relationship with a logarithmic model. This relationship is termed the Arc of Price Responsiveness. We find that for a given price ratio, experiments with enabling technologies tend to produce larger peak reductions, and display a more price-responsive Arc.

Sidebar: The Dynamic Rates

[2] For an early summary, see Ahmad Faruqui and J. Robert Malko, "The Residential Demand for Electricity by Time-Of-Use: A Survey of Twelve Experiments with Peak Load Pricing," *Energy*, Volume 8, Issue 10, October 1983. For more recent surveys, see Ahmad Faruqui and Jenny Palmer, "Dynamic Pricing and its Discontents," *Regulation*, Fall 2011 and Ahmad Faruqui and Sanem Sergici, "Household Response to Dynamic Pricing of Electricity – A Survey of 15 Experiments," *Journal of Regulatory Economics*, October 2010. Faruqui and Palmer also discuss the more common myths that surround legislative and regulatory conversations about dynamic pricing.

[3] Most dynamic pricing studies have included multiple tests. For example, a pilot could test a TOU rate and a CPP rate and it could test each rate with and without enabling technology. Thus, this pilot would include a total of four pricing tests.

[4] See, for example, the concluding remarks in an otherwise excellent paper by Paul Joskow, "Creating a smarter U.S. electrical grid," *Journal of Economic Perspectives*, Winter 2012.

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Time-of-Use (TOU). A 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. 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, mirroring the variation in marginal costs by pricing period.

Critical Peak Price (CPP). On a 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 technology is provided, these rates can also be activated on a day-of basis.

Peak Time Rebate (PTR). If a CPP tariff cannot be rolled out because of political or regulatory constraints, some parties have suggested the deployment of peak-time rebate. 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 through at the existing rate. There is no rate discount during non-event hours. Thus far, PTR has been offered through pilots, but default (opt-out) deployments have been approved for residential customers in California, the District of Columbia and Maryland.

Real Time Pricing (RTP). Participants in 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.

The Dynamic Pricing Studies

The *D-Rex* Database contains the results of 129 dynamic pricing tests from 24 pricing studies. [5] As shown in Figure 1, these results range from close to zero to up to 58 percent. Part of the variation in impacts comes simply from the fact that different rate types are being tested. Filtering by rate in Figure 2, some trends begin to emerge. We observe that the Critical Peak Pricing (CPP) rate tends to have higher impacts than Time-of-Use (TOU) rates, likely because the CPP rates have higher peak to off-peak price ratios. We can also filter by the presence of enabling technology, as in Figure 3, and observe that for the same rates, the impacts with enabling technologies tends to be higher.

[5] 23 of the 24 studies are pricing pilots. The other study is PG&E's full scale rollout of TOU and SmartRate.

Figure 1. Impacts from Residential Dynamic Pricing Tests, Sorted from Lowest to Highest

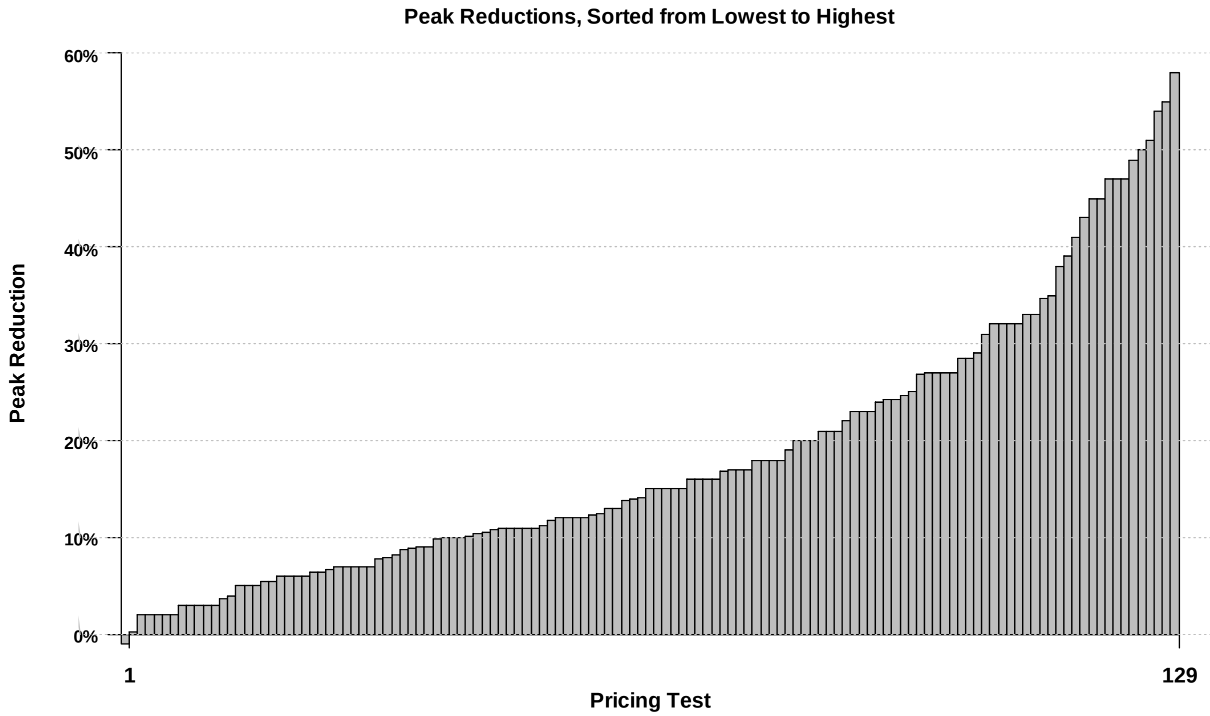
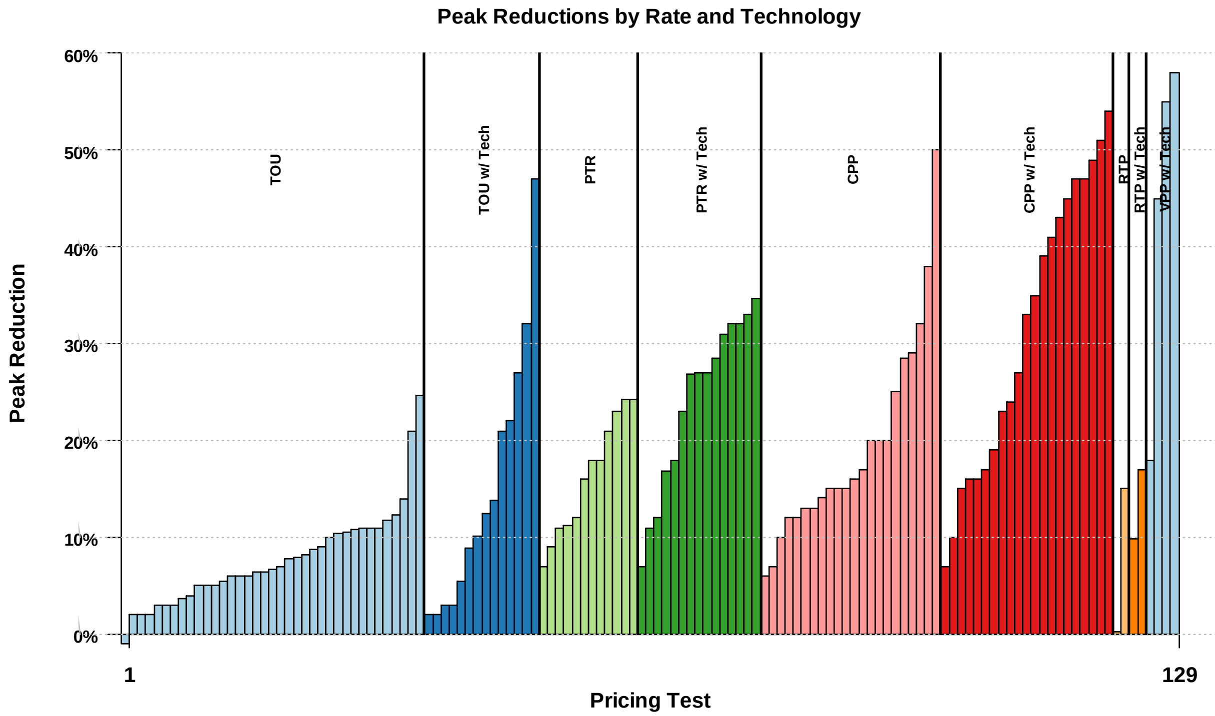


Figure 2. Impacts from Pricing Tests, by Rate Type

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



Even with the rate and technology filters, there remains significant unexplained variation. In order to understand the cause of this variation, we first limit the sample to only the best-designed studies which have reported the relevant data. We selected studies in which samples are representative of the population and the results are statistically valid. Moreover, we selected studies in which participants were selected randomly, as opposed to volunteers responding to a mass mailing. The nine best-designed pilots, shown in Table 1, include 42 price-only tests and 32 pricing tests with prices *cum* enabling technology.[6] In these 74 tests, the peak reductions range from 0% to just under 50%. The remainder of this paper focuses on explaining the variation in these results.

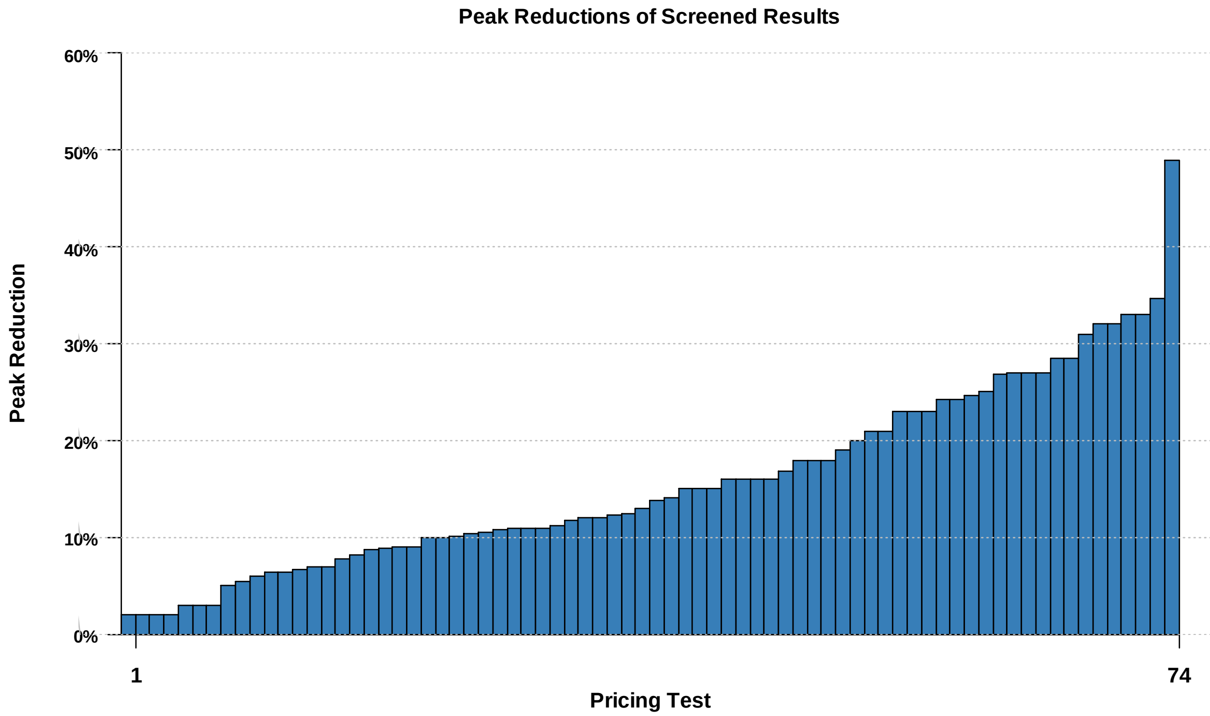
[6] OG&E was not included in these screened results because only the draft results are available thus far. When these results are finalized, they will be included in this analysis.

Table 1. Features of the Nine Dynamic Pilots

Utility	Location	Year	Rates	Enabling Technologies	Number of Tests
Baltimore Gas & Electric	Maryland	2008, 2009, 2010	CPP, PTR	CPP w/ Tech, PTR w/ Tech	17
Connecticut Light & Power	Connecticut	2009	TOU, CPP, PTR	TOU w/ Tech, CPP w/ Tech, PTR w/ Tech	18
Consumers Energy	Michigan	2010	CPP, PTR	CPP w/ Tech	3
Pacific Gas & Electric (Full scale rollout)	California	2009, 2010	TOU, CPP	Not tested	4
Pacific Gas & Electric, San Diego Gas & Electric, Southern California Edison (Statewide Pricing Pilot)	California	2003, 2004	TOU, CPP	CPP w/ Tech	4
Pepco DC	District of Columbia	2008, 2009	CPP, PTR, RTP[2]	CPP w/ Tech, PTR w/ Tech, RTP w/ Tech	4
Salt River Project	Arizona	2008, 2009	TOU	Not tested	2
Utilities in Ireland[2]	Ireland	2010	TOU	TOU w/ Tech	16
Utilities in Ontario	Ontario, Canada	2006	TOU, CPP, PTR	Not tested	6
				Total	**74**

1. Run by the Commission for Energy Regulation (CER)
2. The two RTP pricing tests are excluded from this analysis because they do not have a clear peak to off-peak price ratio.

Figure 4. Impacts from Pricing Tests, by Rate Type and Presence of Enabling Technologies

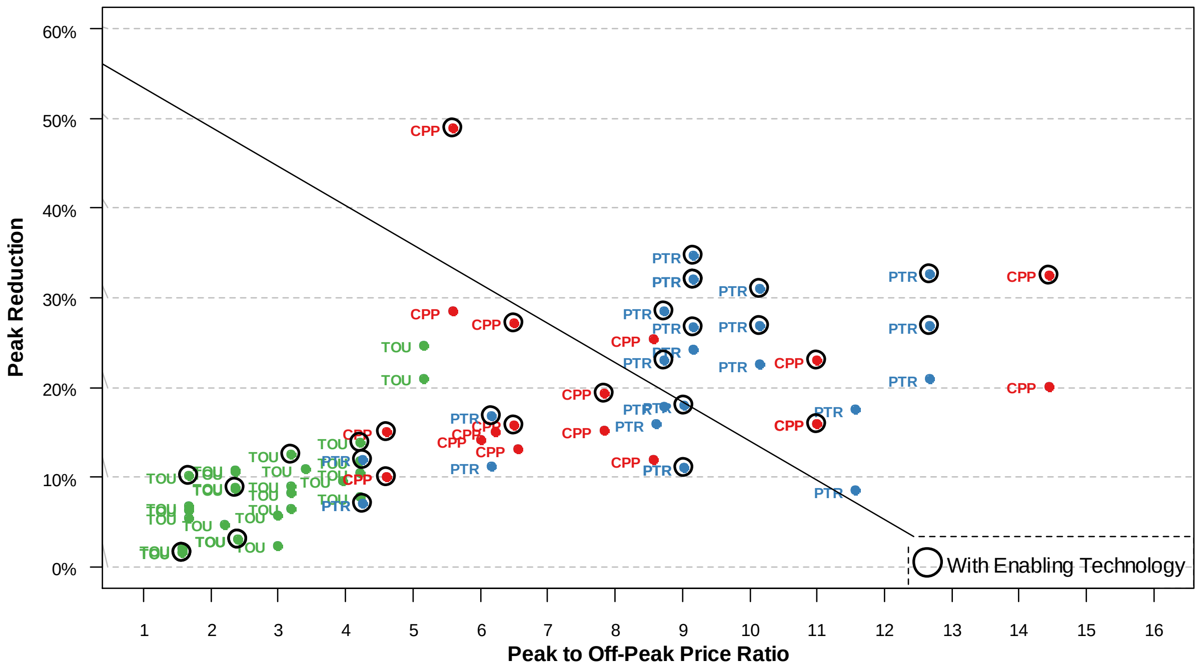


Methodology

The nine best-designed studies in *D-Rex* include 42 price-only test results and 32 price-cum-enabling technology test results for a total of 74 observations. For each result, we plot the all-in peak to off-peak price ratio against the corresponding peak reduction. As expected, the CPP and PTR rates tend to have higher peak to off-peak ratios than the TOU rates, with some overlap, and those rates with higher price ratios tend to yield greater peak reductions.[7] It also appears that that the enabling technology impacts may be greater than those with price only.

[7] For the PTR rate, the effective critical peak price is calculated by adding the peak time rebate to the rate that the customer pays during that time period.

Figure 5. Impacts from Pricing Tests by Peak to Off-Peak Ratio, Showing Rate Type and Presence of Enabling Technologies



The plot suggests that peak impacts increase with the price ratio but at a decreasing rate. The logarithmic model would model rapid increases in peak reduction in the lower price ratios, followed by slower growth.[8]

Logarithmic Model

$$y = a + b * \ln(price\ ratio)$$

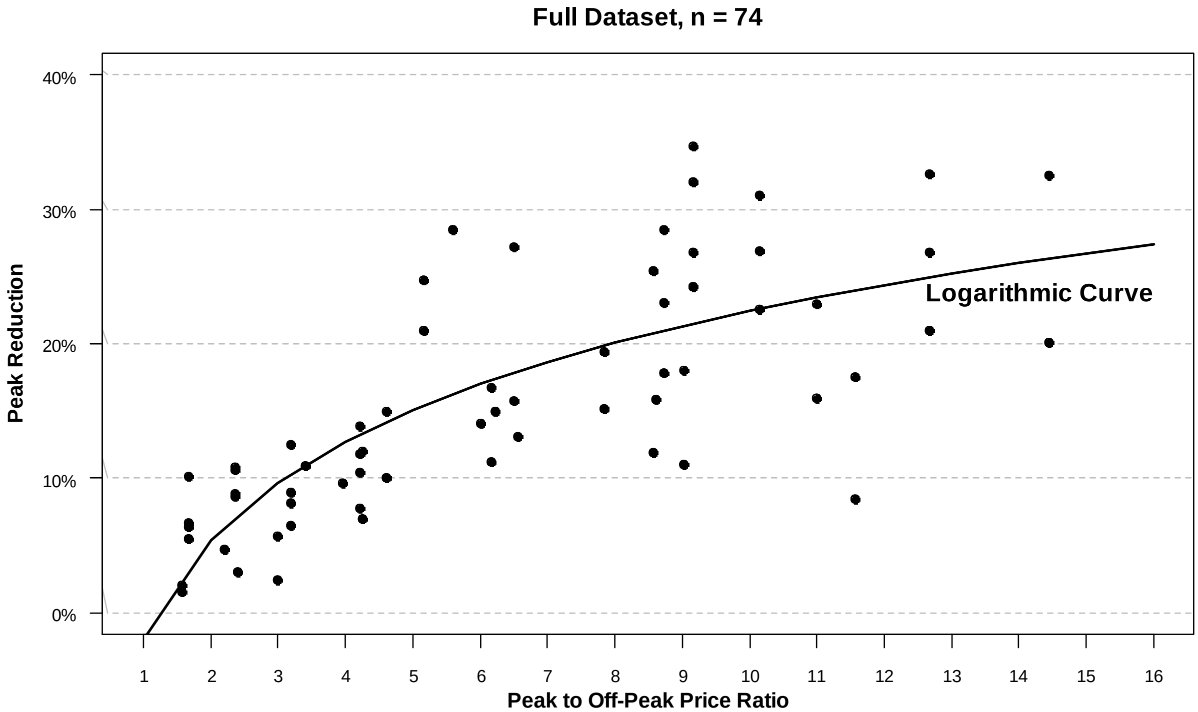
where $y = peak\ reduction\ percent$

Results

When we fit the logarithmic model to the full dataset (n = 74), it yields a coefficient of 0.106 with a standard error of 0.012, significant at the 0.001 level. In other words, as the price ratio increases, the peak reduction is also expected to increase. The peak-to-off-peak price ratio successfully explains 49 percent of the variation in demand response. The logarithmic curve suggests that if the peak to off-peak price ratio were to get as high as 16, the peak reduction could be close to 30 percent.

[8] We also considered a logistic growth model that features slow growth at lower price ratios followed by moderate growth, followed by an upper bound peak reduction. The results were not significantly different with this functional form.

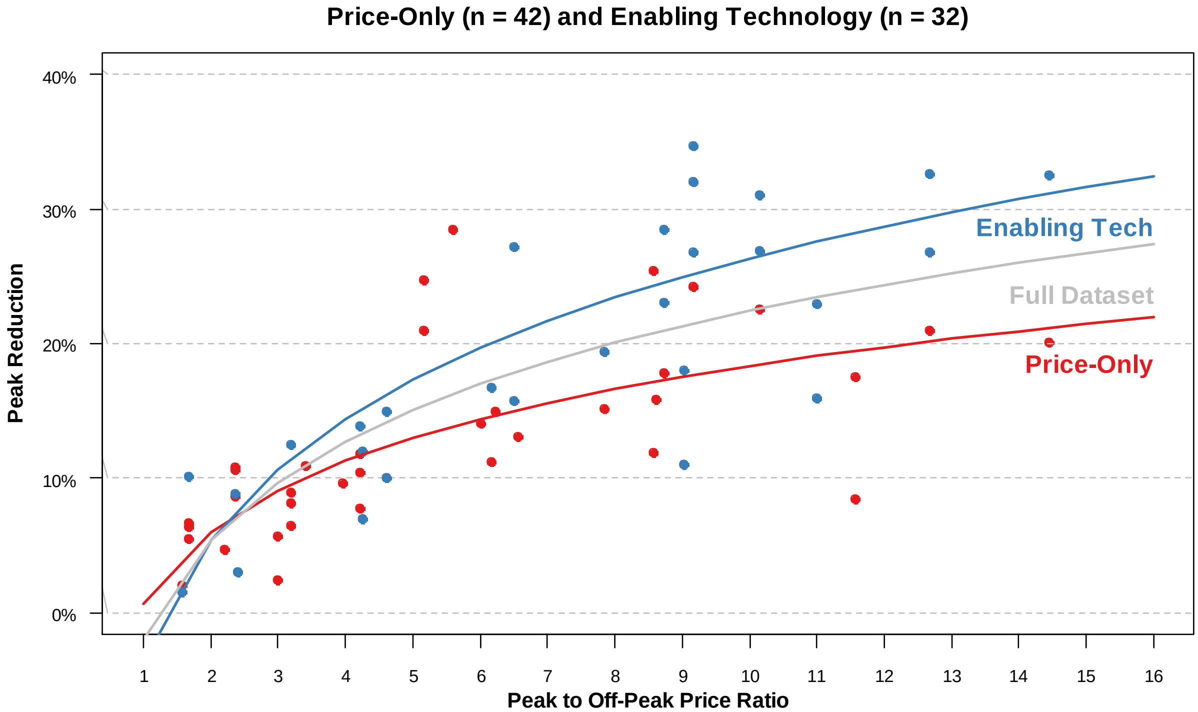
Figure 6. Impacts from Pricing Tests by Peak to Off-Peak Ratio with the Fitted Logarithmic Curve



We can narrow down the model to focus on the price-only observations separately from the enabling technology observations. With this data, the model yields a coefficient of 0.077 with a standard error of 0.012, again significant at the 0.001 level. The coefficient is slightly lower here than in the full dataset, suggesting that the impacts increase more slowly in the absence of enabling technology. In this case, the adjusted R-squared value is 48 percent, meaning the ratio again explains almost half of the variation in response. The logarithmic curve suggests that if the peak to off-peak price ratio were to get as high as 16, the peak reduction would be slightly over 20 percent.

With the enabling technology tests, we find that the curve has a steeper slope than the result with price-only tests. The coefficient of the enabling technology curve is 0.130 which has a standard error of .02. The regression successfully explains 53 percent of the variation in demand response. With a peak to off-peak ratio of 16, the peak reduction is expected to be over 30 percent.

Figure 7. Impacts from Pricing Tests by Peak to Off-Peak Ratio with the Fitted Logarithmic Curves, Segregated by Presence of Enabling Technologies



The full regression results for the three different data specifications are shown in Table 2 below. In each case, the coefficient on the natural log of the price ratio is positive and significant at the 0.001 level.

Table 2. Regression Results

Coefficient	Full Dataset		Price-Only		Enabling Technology	
Ln(Price Ratio)	0.10611	***	0.07682	***	.13029	***
	(0.01254)		(0.01220)		(0.02164)	
Intercept	-0.01985		0.00654		-0.03668	
	(0.02234)		(0.02071)		(0.04080)	
Adjusted R-Squared	0.4916		0.4852		0.532	
F-Statistic	71.59		39.65		36.24	
Observations	74		42		32	

Standard errors are shown in parentheses below the estimates
*** = 0.001 significance
** = 0.01 significance
* = 0.05 significance

Conclusion

In our view, the results presented in this paper provide strong support for the deployment of dynamic pricing. They conclusively show that customers are responsive to changes in the price of electricity. In other words, they lower demand when prices are higher. Moreover, the results suggest that the presence of enabling technology allows customers to increase their peak reduction even further. These results may be used to quantify the potential peak reductions that may be expected when new dynamic rates are rolled out and to monetize these benefits using estimates of the avoided capacity of capacity and energy.[9]

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[9] On the monetization of benefits arising from smart meters and dynamic pricing in the context of the EU, see Ahmad Faruqui, Dan Harris, and Ryan Hledik, "Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment," *Energy Policy*, 2010.

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Biography of Authors

Ahmad Faruqui is a principal with The Brattle Group. He has been analyzing time-varying experiments since the beginning of his career in 1979 and his early work is cited in the third edition of Professor Bonbright's canon on public utility ratemaking. The author of four books and more than a hundred papers on energy policy, he holds a doctoral degree in economics from the University of California at Davis and bachelor's and master's degrees from the University of Karachi.

Jennifer Palmer is a research analyst at The Brattle Group. Since joining The Brattle Group in 2009, she has worked with a wide range of utilities on dynamic pricing and advanced metering projects. For several utilities, she has developed dynamic tariffs, simulated the impacts of these rates on customer consumption patterns, and estimated the resulting system-level benefits. She has a bachelor's degree in economics with a certificate in environmental studies from Princeton University.

Appendix

Impacts from Pricing Tests by Peak to Off-Peak Ratio, Showing Utility Names