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Arcturus 2.0: A Meta-Analysis of Time-Varying Rates for Electricity

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With the rapid deployment of smart meters, utilities and regulators across the globe are considering the deployment of time-varying rates for residential customers. Ontario, Canada, has deployed time-of-use rates in the province for several years. California plans to deploy time-of-use rates as the default tariff beginning in 2019. However, many observers still disagree on the magnitude of demand response that would be induced by time-varying rates, such as time-of-use rates, critical peak pricing rates, peak time rebates and real-time pricing. Our analysis of the impact of several studies of time-varying rates from across the globe finds that much of the discrepancy in results across the studies goes away once demand-response is expressed as a function of the peak to off-peak price ratio. We find that customers do respond to higher peak to off-peak price ratios by lowering their peak demand, and this effect is amplified by the presence of enabling technologies. We also find that there are diminishing returns to dialing up the peak to off-peak price ratio beyond a certain threshold.

Introduction

The first wave of time-varying rates studies began in the 1970s when twelve pricing experiments were carried out in the US. They were administered by the Federal Energy

[1] The authors are economists with The Brattle Group. They are grateful for comments on early drafts of the paper by several people, including Neil Lessem, Ryan Hledik and Phil Hanser. They are also very grateful to the authors of the studies whose results made it possible to build the Arcturus database and to carry out the meta-analysis that is presented in the paper. This paper reflects the views of the authors and not necessarily the views of their employer. Comments can be directed to ahmad.faruqui@brattle.com.

Administration, a predecessor to the U.S. Department of Energy.[2] Approximately 7,000 customers were enrolled in the first wave. Although the results were promising, the quality of the experimental designs in many cases left much to be desired and thus the results were not of immediate use by regulators, policy makers and utilities.

The second wave of studies came in the mid-1980s, when the Electric Policy Research Institute (EPRI) reexamined the results of the five most promising pilots from the first wave and found consistent evidence of demand response across the five studies. However, in the absence of smart meters, the momentum was lost. As the industry began to restructure in the mid-to-late 1990s, time-varying rates were given low priority and next to nothing happened for two decades.

California's energy crisis of 2000-01 triggered renewed interest in the topic. Time-varying rates were judged by many experts and the regulators in California in particular to be a good way to link retail and wholesale markets and prevent a recurrence of the energy crisis. The argument was made that if customers had an incentive to reduce usage during costly peak periods, demand and supply would come into balance automatically and avert the need for administrative solutions to avert a crisis.

In the third wave, the pilots were expanded to include enabling technologies like smart thermostats and in-home displays. The third wave also incorporated dynamic rate designs that went beyond the traditional time-of-use (TOU) structure, such as critical-peak pricing (CPP), peak-time rebate (PTR), and variable-peak pricing (VPP).

The fourth wave of pilots will likely evolve to incorporate demand charges. Over 30 utilities in the U.S. currently offer residential demand charges, and more utilities are interested in expanding them to their residential customer base. In a recent general rate case, Arizona Public

[2] Faruqui, Ahmad and J. Robert Malko, "The residential demand for electricity by time-of-use: A survey of twelve experiments with peak load pricing," *Energy* 8:10, 1983, pp. 781-795.

Service, which has about 10% of its customers on a demand charge, had proposed deploying demand charges on a default basis for its residential customers. Earlier, Oklahoma Gas & Electric had made a similar proposal for all those customers but who were on the company's Smart Hours program, a VPP rate.

Over time, we have built a database of the results from dynamic pricing deployments from around the globe. It is called Arcturus, since the results take the form of arcs of price response. We believe this is the largest repository of time-varying rate designs in the world. Its contents are drawn mostly from the third wave, whose studies feature almost 1.4 million customers, compared to the first wave's 7,000 customers. It also includes the results from Ontario's default deployment of TOU rates to the four million customers in the province. Results are also included from a study that was done on Italy's default TOU rate deployment to some 25 million customers.[3]

Arc 1.0 and Arc 2.0 Comparison

Faruqui and Sergici published the first analysis of the Arcturus database in this journal in 2013.[4] Due to growing industry interest in dynamic pricing, Arcturus has more than doubled in size since then. In 2013, Arcturus 1.0 contained 163 experimental pricing treatments from 34 pilots. Arcturus 2.0 contains 337 treatments from 63 pilots. Arcturus 2.0 also contains information from two additional countries. Arcturus 2.0 features new categorical information

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[3] Presented by Walter Graterri and Simone Maggiore, "Impact of a Mandatory Time-of-Use Tariff on the Residential Customers in Italy," Ricerca Sisterna Energetico, November 14-16, 2012, available: http://www.ieadsm.org/wp/files/Content/14.Espoo_IEA_DSM_Espoo2012_SimoneMaggiore_RSE.pdf

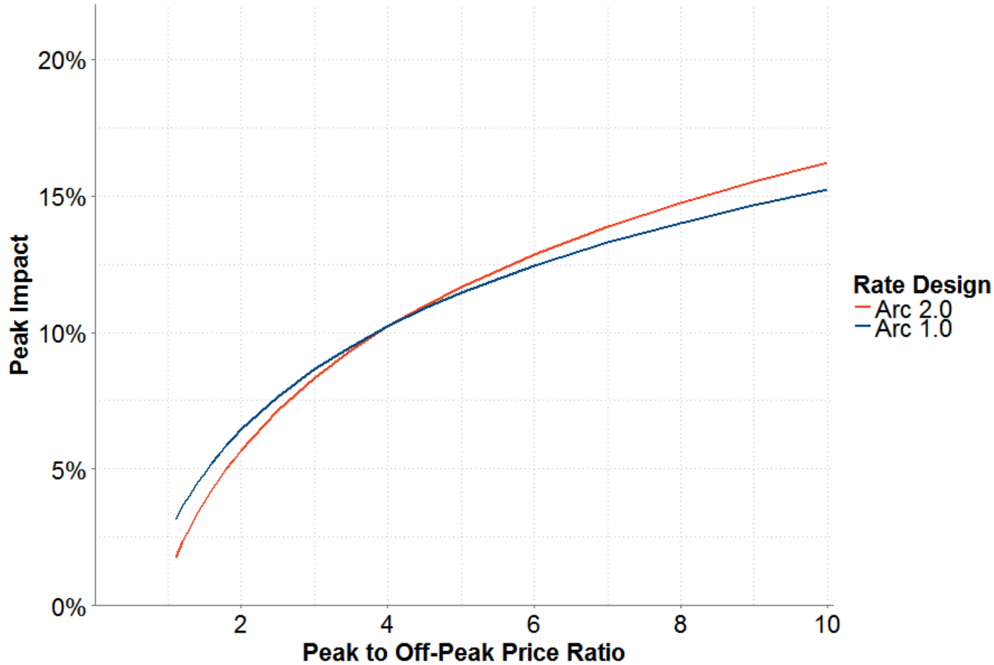
[4] Faruqui, Ahmad and Sanem Sergici, "Arcturus: International Evidence on Dynamic Pricing," *The Electricity Journal*, August/September 2013.

about the pilots as well, including details on the duration of each rate design's peak hours, whether the pilot was administered on an opt-in or opt-out basis, and if the pilot measured impacts in the summer, winter, or both. Finally, it contains pilots that offer the latest types of enabling technologies. For example, in 2016, San Diego Gas & Electric offered the Ecobee Smart Si thermostat to customers on its peak-time rebate program.[5] The Ecobee Smart Si thermostat allows a residential customer to monitor and control his or her energy usage remotely from a smartphone or computer. Additionally, some Ecobee thermostats are compatible with Amazon's voice-enabled home assistant, Alexa. This allows customers to more easily set their thermostats' cycling tendencies.

For comparison, the results of Arcturus 1.0 and Arc 2.0 are plotted together in **Figure 1**. The curves were estimated using regression analysis, and the estimation is described in further detail later in this paper. **Figure 1** shows that the slope of Arcturus 2.0 is slightly steeper than its predecessor. This implies there are greater gains to customer load-shifting from incremental increases in the peak-to-off-peak price ratio. However, the intercept on Arcturus 1.0 is higher than Arcturus 2.0, which means Arcturus 1.0 estimates greater peak reductions than Arcturus 2.0 until a price ratio of approximately four.

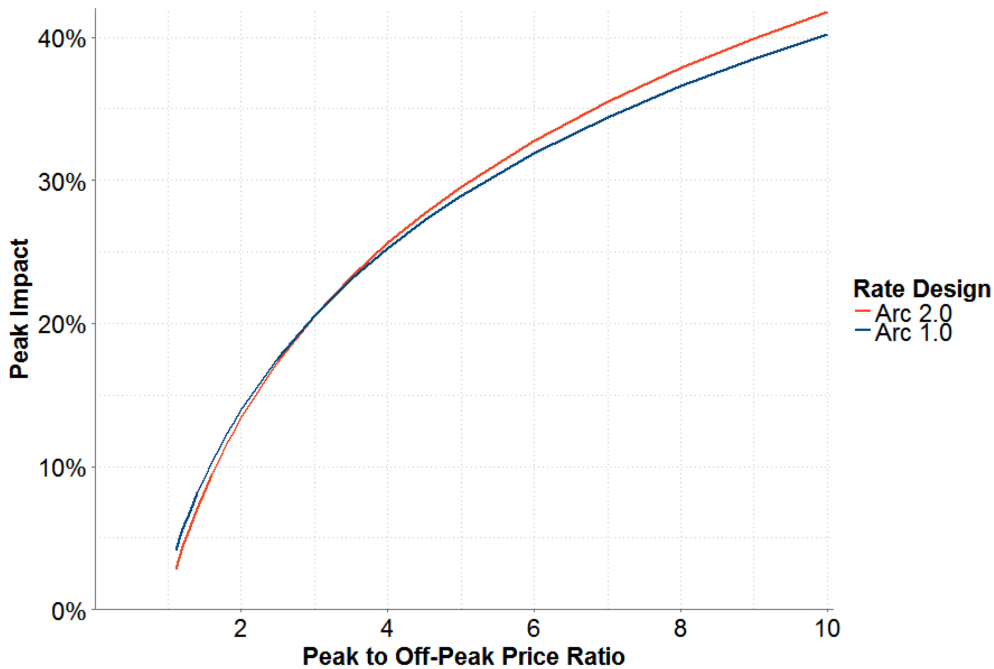
[5] Itron, Inc., "2016 Impact Evaluation of San Diego Gas & Electric's Residential Peak Time Rebate and Small Customer Technology Deployment Programs," March 20, 2017, available: http://www.calmac.org/publications/SDGE_PTR_2016_Final_Report.pdf

Figure 1: Comparison of Arcturus 1.0 (2013) and Arcturus 2.0 (2017) Experimental Treatments without Enabling Technology



The curves in **Figure 1** do not include the effect of enabling technologies like smart thermostats. As discussed later in this paper, enabling technologies enhance a customer's ability to reduce peak demand. Similar to **Figure 1, Figure 2** compares Arcturus 1.0 and Arcturus 2.0 for treatments that feature enabling technology. Just like **Figure 1**, the slope of Arcturus 2.0 is slightly steeper than Arcturus 1.0.

Figure 2: Comparison of Arcturus 1.0 (2013) and Arcturus 2.0 (2017) Experimental Treatments with Enabling Technology



One notable difference between Arcturus 1.0 and the model presented in this paper is the incremental impact of enabling technology. Arcturus 1.0 estimates, on average, that a customer assisted by enabling technology will reduce his or her peak usage by 5.4% more than a customer without enabling technology. In contrast, Arcturus 2.0 estimates an incremental effect of 4.6%, which is almost a percentage point less than the original Arcturus. The details of the Arcturus 2.0 estimation, including summaries of the dataset and the model specification, are discussed in the following sections.

The Studies

Spanning four continents, Arcturus contains 337 experimental and non-experimental pricing treatments from over 60 pilots. The pricing experiments typically take the form of a treatment group that is enrolled on a time-varying rate and a control group that remains on a standard residential rate. The purpose of the experiment is to measure how much customers reduce their electricity usage during peak-hours in comparison to a control group.

The studies begin as early as 1997, and the most recent study was published in 2017. Only pilots that adhere to the rigorous standards of experimental research design are added to the database. Similarly, results from pricing treatments that are not statistically significant at acceptable levels are deemed to have no effect.[6] **Figure 3** shows how interest in time-varying pricing experiments has grown considerably over the last twenty years. Specifically, **Figure 3** plots the number of cumulative pricing treatments by year. Each pilot consists of one or more pricing treatments. For example, Xcel Energy carried out a pilot from October 2010 to September 2013 that introduced customers in Boulder, Colorado to a variety of TOU, CPP, and PTR pricing treatments.[7] The single pilot reported impacts for sixteen pricing treatments.

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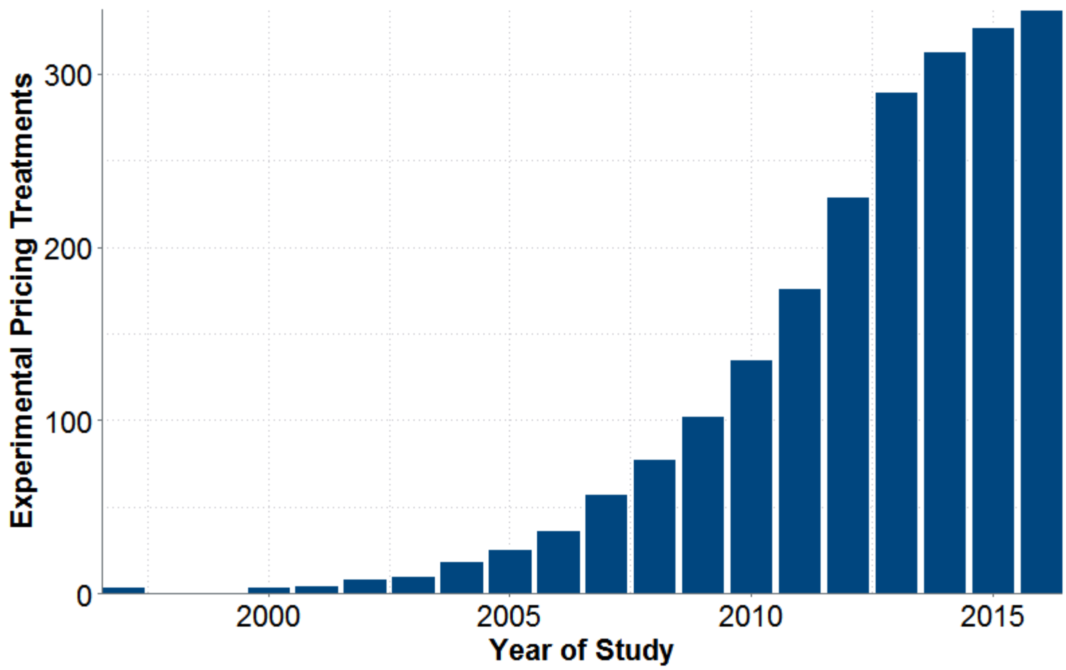
[6] These pricing experiments are excluded from the model's estimation of customer impacts but are included in the bar charts below.

[7] Gouin, Andre and Craig Williamson, "SmartGridCity Pricing Pilot Program: Impact Evaluation Results, 2011 – 2013," prepared for Xcel Energy, December 6, 2013, available: http://s3.amazonaws.com/dive_static/diveimages/SGC_Pricing_Pilot_Evaluation_Report_FINAL-1.pdf

Figure 3: Cumulative Pricing Treatments

Arcturus Database



Arcturus contains four different types of time-varying rate designs: TOU, CPP, PTR, and VPP, with the majority being TOU rate designs. These types of designs break up the day into two or more periods and charge a higher price per kWh in one period in comparison to the other(s). The higher price period is known as the peak-period and the lower price period is known as the off-peak period. The differential between prices in the peak-period and off-peak period are typically designed to reflect the marginal costs a utility incurs for producing electricity. TOU rate designs may also break up the calendar year into seasons and charge a higher price in the summer months and a lower price in the winter months for summer-peaking utilities.

The second and third rate designs contained in Arcturus are CPP and PTR. These two differ from TOU designs in that the higher price periods are not known well in advance. Under a

CPP or PTR structure, the utility notifies customers a day in advance and sometimes on the day of the event. In much of the U.S., peak events typically coincide with the hottest days of the summer when load from residential air-conditioning drives up forecasted peak demand. Many of the pilots planned to hold at least ten event days during the study period and at most fifteen. Sometimes, the study period was uncharacteristically cool, leading to fewer event days during the study period. On an event day, CPP charges customers a peak price that is often several multiples of the off-peak price. In some cases, the critical peak price exceeds $1 per kilowatt-hour. Similarly, a PTR rate design resembles CPP, except customers receive a rebate for shifting on-peak usage to the off-peak hours rather than paying a higher rate. No discount is offered during the off-peak periods and the standard tariff applies during all hours.

VPP is the fourth and final rate design contained in Arcturus. During the peak period, customers are charged a rate that varies by the utility and usually mimics the wholesale price of electricity. In this way, VPP is a hybrid of a TOU rate design and real-time pricing. Because peak-prices mimic the market prices for electricity, VPP rate designs more accurately match the utility's cost of producing electricity. As seen in **Figure 4**, there are fewer VPP rate designs than TOU, CPP, and PTR rate designs.

Figure 4: Summary of Rate Designs

Arcturus 2.0

		Season			Recruitment		
Rate Design	**N**	**Summer Only Rate**	**Winter Only Rate**	**Annual Rate**	**Opt-In**	**Opt-Out**	**Peak Hours Greater Than 4**
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
TOU	153	59%	19%	22%	75%	25%	64%
CPP	105	70%	6%	25%	90%	10%	36%
PTR	64	91%	5%	5%	91%	9%	52%
VPP	15	87%	7%	7%	100%	0%	60%
All	337	69%	12%	19%	84%	16%	53%

Nearly three-quarters of the studies in Arcturus were conducted during the summer months. Often, utilities conduct these pilots during the summer months because they are summer-peaking utilities and can benefit most from peak reductions in the summer months. However, there are winter-peaking utilities in New Zealand and Ontario that have conducted their studies during winter months.

Figure 4 also shows that 84% of the treatments are based on an opt-in recruitment design. It is politically challenging to administer a pilot on an opt-out (or default) design because customers may be resistant to enrollment on an experimental rate without prior consent. This is an important point because the peak impacts of a full-scale deployment are more likely to resemble the effects of an opt-out design rather than opt-in. Under an opt-in design, the customers who enroll in the experimental rate are typically more conscious of their energy usage and are typically more conservation-minded. Faruqui, Hledik, and Lessem (2014) show that although default rate designs result in smaller impacts per customer, the aggregate peak impacts are higher compared to opt-in rate designs.[8] The higher aggregate impacts come from the higher enrollment rates under a default rate. Under a default rate, customers are less likely to actively opt-out of the dynamic rate design and thus stay on the rate by default. In contrast, opt-in rates require utilities to actively market the rate product and recruit customers for enrollment. This is a costly process and results in aggregate enrollment rates that are lower than default rate designs. The Smart Pricing Options Pilot administered by Sacramento Municipal Utility District includes a detailed study of the impacts of default TOU and CPP rate designs.[9]

Arcturus also contains data on each pricing treatment's peak period duration. **Figure 4** shows that half of the experimental treatments feature peak periods that are greater than four hours. On average, the duration of CPP rates are much shorter than the other types of rate designs. Only a third of CPP rate designs feature peak periods lasting more than four hours. For the most part, each pilot's peak period lasted from three to five hours. However, in rare cases, some pilots featured peak periods lasting more than ten hours.

Research Hypothesis

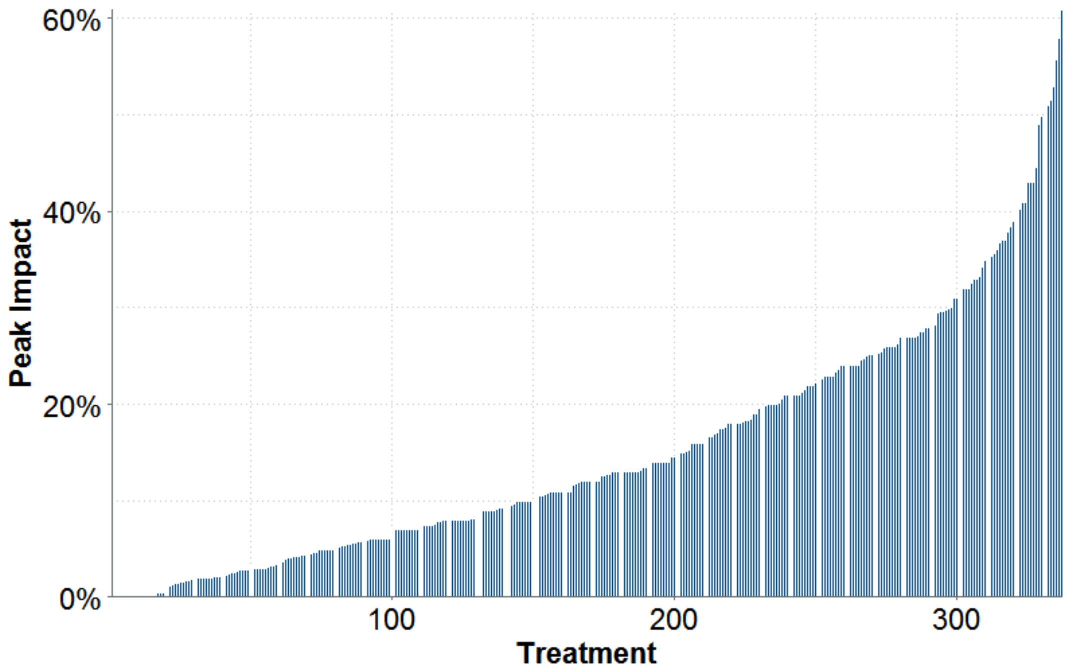
Our meta-analysis examines two fundamental questions. First, do customers respond to dynamic pricing by reducing their peak usage? Second, if customers do respond, is the treatment effect stronger in the presence of enabling technology? The depth of Arcturus allows us to explore such a hypothesis. **Figure 5** ranks the peak impact of each experimental treatment from lowest to highest. It is clear that there is a wide range of peak impacts in Arcturus. For this

[8] Ahmad Faruqui, Ryan Hledik, and Neil Lessem, "Smart by Default," *Public Utilities Fortnightly*, August 2014, available: https://www.fortnightly.com/fortnightly/2014/08/smart-default

[9] Potter, Jennifer M., Stephen S. George, and Lupe R. Jimenez, "SmartPricing Options Final Evaluation," prepared for U.S. Department of Energy, September 5, 2014, available: https://www.smartgrid.gov/files/SMUD_SmartPricingOptionPilotEvaluationFinalCombo11_5_2014.pdf

reason, the results shown in **Figure 5** do not provide conclusive answers to our research questions. Several peak impacts are no more than two percent while others exceed fifty percent.

Figure 5: Pricing Treatments by Rank



After grouping the treatments by those that use enabling technology and those that do not, it is easier to detect a pattern in the results. Enabling technologies include devices that provide a customer with the ability to actively manage their electricity usage, particularly during the peak period. For example, Australia's Smart Grid Smart City project used Energy Aware's in-home display to communicate usage amounts and real-time prices to households.[10] The utility could send text messages to the display to inform the customer about price changes and peak events. Additionally, the display shows the current price of electricity and enables the customer to reduce peak usage when prices are high. **Figure 6** shows the distribution of peak impacts

[10] AEFI Consulting Consortium, "Smart Grid, Smart City: Shaping Australia's Energy Future, National Cost Benefit Assessment," July 2014.

among treatments without enabling technology, and **Figure 7** shows the distribution of peak impacts among treatments with enabling technology.

Figure 6: All Treatments without Enabling Technology

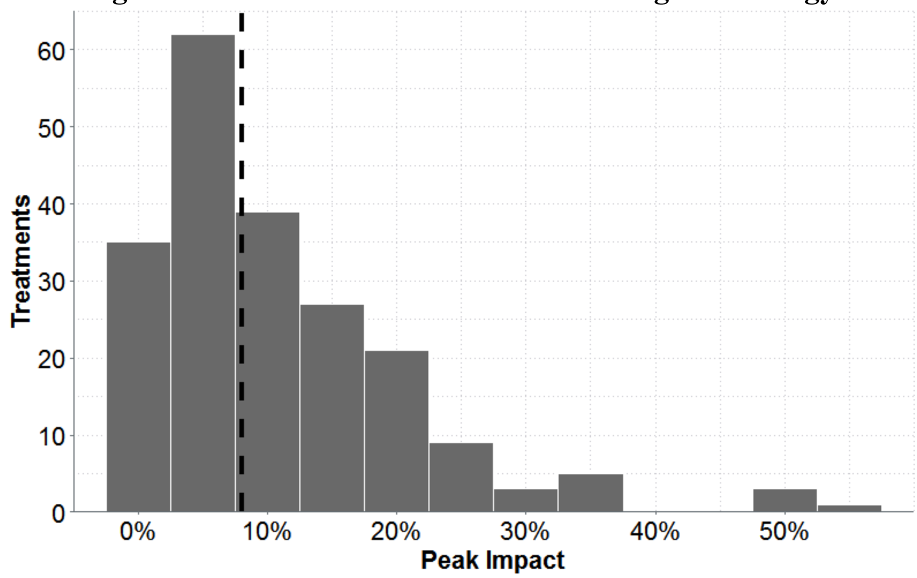
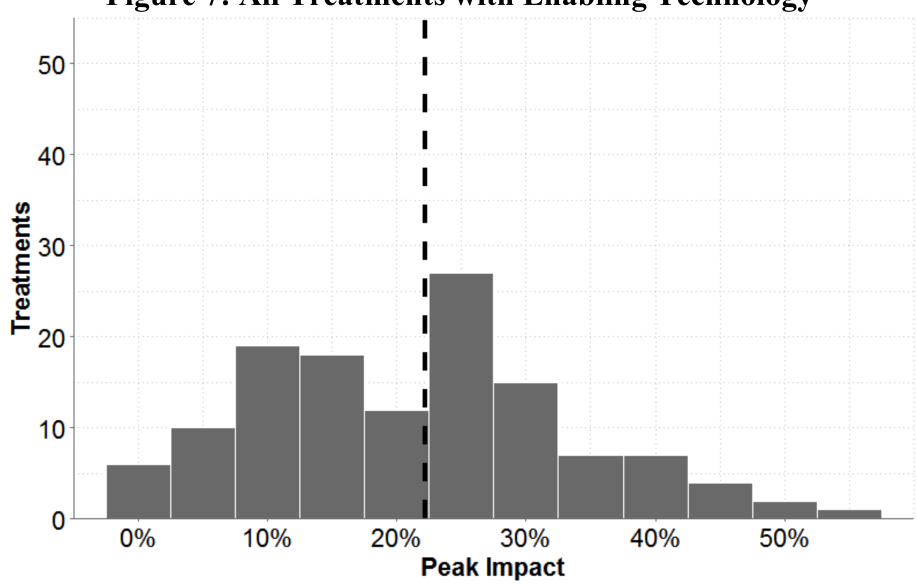
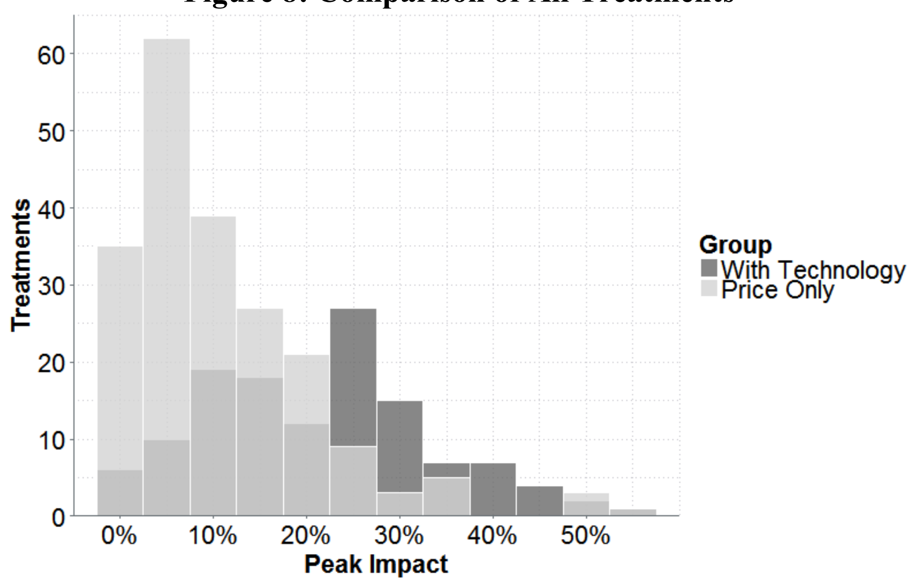


Figure 7: All Treatments with Enabling Technology



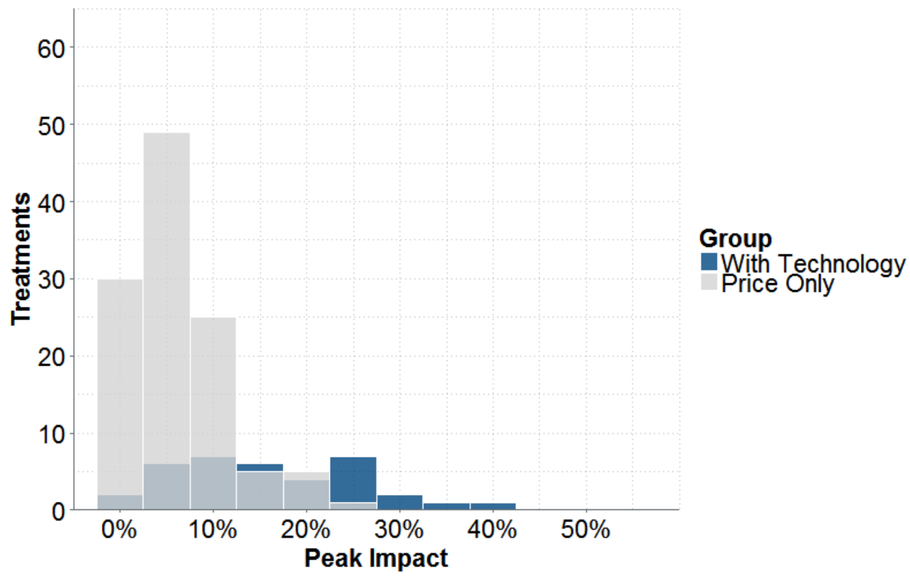
In **Figure 6**, the distribution of peak impacts is clustered below a peak impact of twenty percent. In contrast, **Figure 7** features a wider distribution of peak impacts that are not clustered closely together like in **Figure 6**. This can be partly explained by the variation in the enabling technologies as well as the control strategies adopted in different experiments. The wider distribution in **Figure 7** is also consistent with the hypothesis that enabling technology increases a customer's response to a price signal. **Figure 8** overlays both of these distributions and shows that there is a clear distinction between the two types of treatments.

Figure 8: Comparison of All Treatments



This hypothesis is verified within each type of rate design as well. **Figure 9** compares the distributions of peak impacts for TOU rate designs with and without enabling technology. TOU rate designs that do not implement enabling technology result in peak impacts that are clustered at the ten percent mark or lower. In contrast, TOU rates that feature enabling technology result in a wider distribution of peak impacts. The intuition behind these results is that a customer with an in-home display is more likely to turn down his or her air-conditioning unit during peak hours than a customer without an in-home display.

Figure 9: TOU Treatment Comparison



This relationship between enabling technology and peak reductions is also found within CPP and PTR rate designs. **Figure 10** shows the distribution of CPP treatments and **Figure 11** shows the distribution of PTR treatments.

Figure 10: CPP Treatment Comparison

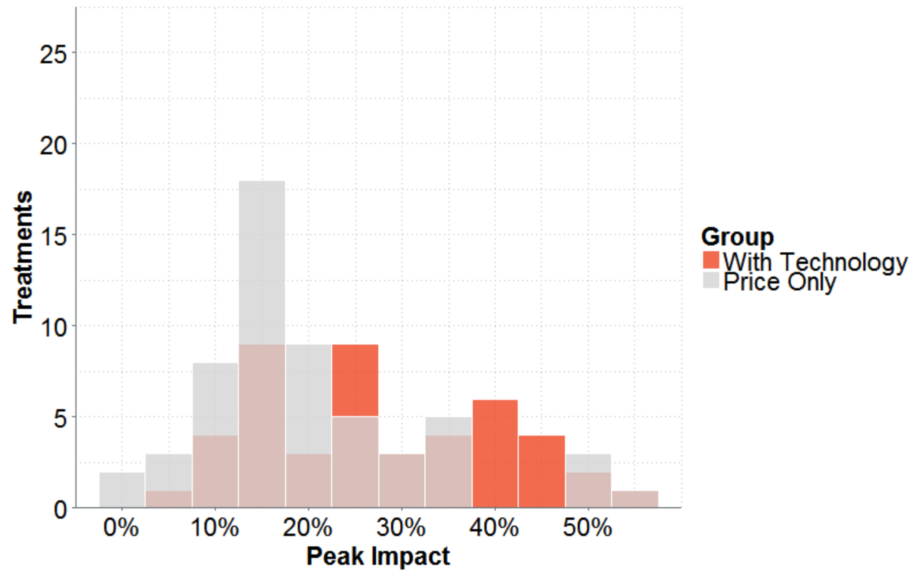
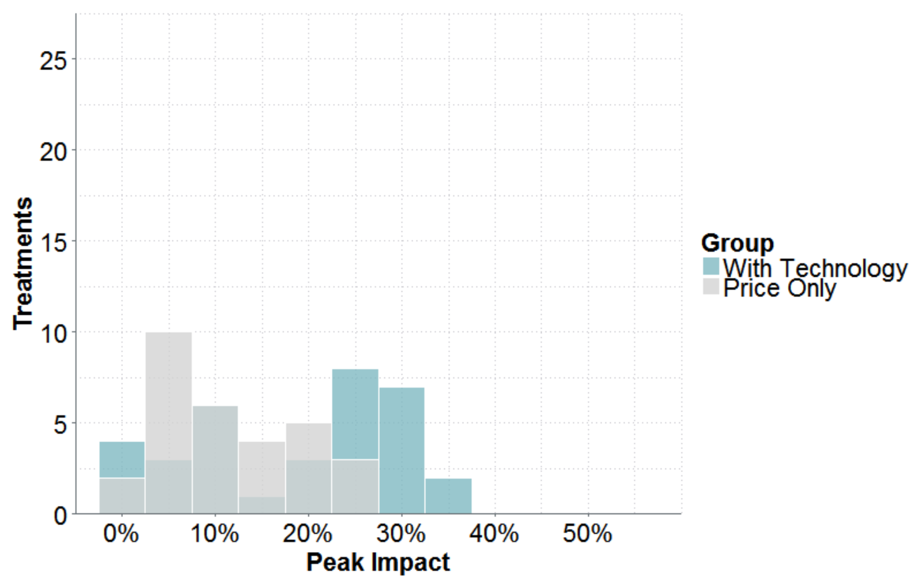


Figure 11: PTR Treatment Comparison



Again, comparing the pricing treatments by technology appears to confirm part of our hypothesis. In the next section, we build a simple econometric model that applies a statistical test to answer the two research questions.

The Arc of Price Responsiveness

Our hypothesis is two-fold. First, customers respond to a price signal by reducing their peak electricity usage. If a customer faces a stronger price signal (a higher on-peak price), then he or she will reduce peak electricity usage even further. Second, if a rate design is accompanied by enabling technology, he or she will reduce his or her peak electricity usage even more. To test this hypothesis, we constructed a simple linear regression model that estimates the effects of the peak to off-peak price ratio and the use of enabling technology. The model is simple because it assumes the peak to off-peak ratio is the primary determinant of variations in peak usage. Other factors, such as weather or income, may influence peak usage but are not included here. However, the simplicity of the model is also one of its strengths. It is easy to interpret and presents peak usage as a simple function of the peak to off-peak price ratio.

The model takes the form of a log-linear specification, in which the amount of the peak reduction is a function of the log of the price ratio.

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

where *y*: peak demand reduction expressed as a percentage;

ln(*price ratio*): natural logarithm of the peak to off-peak price ratio;

ln(*price ratio* * *tech*): interaction of the ln(*price ratio*) and *tech* dummy variable where *tech* takes a value of 1 when enabling technology is offered with price.

Figure 12 presents the results of the model. The coefficient on the log of the price ratio is negative, indicating an inverse relationship between the price ratio and peak usage. Similarly, the coefficient on the interaction between the log of the price ratio and the presence of enabling technology is negative. The value of the coefficient on the log of the price ratio signifies that a 10% increase in the price ratio would result in a 6.5% decrease in peak usage. The same interpretation holds for the coefficient on the technology interaction term. In the presence of enabling technology, a 10% increase in the price ratio results in a 4.6% *incremental* decrease in peak usage, for a total reduction of 11.1%.

The standard errors of the estimated coefficients suggest this relationship is statistically significant. In other words, it is very unlikely that the estimated coefficients are simply a random estimate not statistically distinguishable from zero. The R-squared value indicates that over half of the variation in the percent reduction in peak demand (i.e., demand response) can be explained by the independent variables.

Figure 12: Primary Regression Results

	Dependent variable:
	Peak Impact
Log of Peak/Off-Peak Ratio	-0.065^{***}
	(0.007)
Log of Peak/Off-Peak Ratio x Technology	-0.046^{***}
	(0.008)
Constant	-0.011
	(0.007)
Observations	335
R^2	0.569
Adjusted R^2	0.566
Residual Std. Error	0.064 (df = 332)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The model was estimated using a robust regression technique that down-weights outlying observations. By using MM-estimation, the model ensures that the estimated coefficients are not influenced by pilots that report substantially higher peak impacts.[11] In this analysis, we used the "robustbase" package available through the open-source programming language R to apply the weights to each observation. Also, two pilots tested price ratios that exceeded 35 to 1. Because these ratios are on the extreme end of the sample, they were dropped from the analysis.

In addition to the model specification shown in **Figure 12**, we tested a model that included a binary if the rate design was administered on an opt-out basis. Based on Faruqui, Hledik, and Lessem's (2014) analysis we would expect peak impacts to be lower under an opt-

[11] Yohai, Victor J., "High Breakdown-Point and High Efficiency Robust Estimates for Regression," *The Annals of Statistics* 15:20, 1987, pp. 642-656, available: https://projecteuclid.org/download/pdf_1/euclid.aos/1176350366;

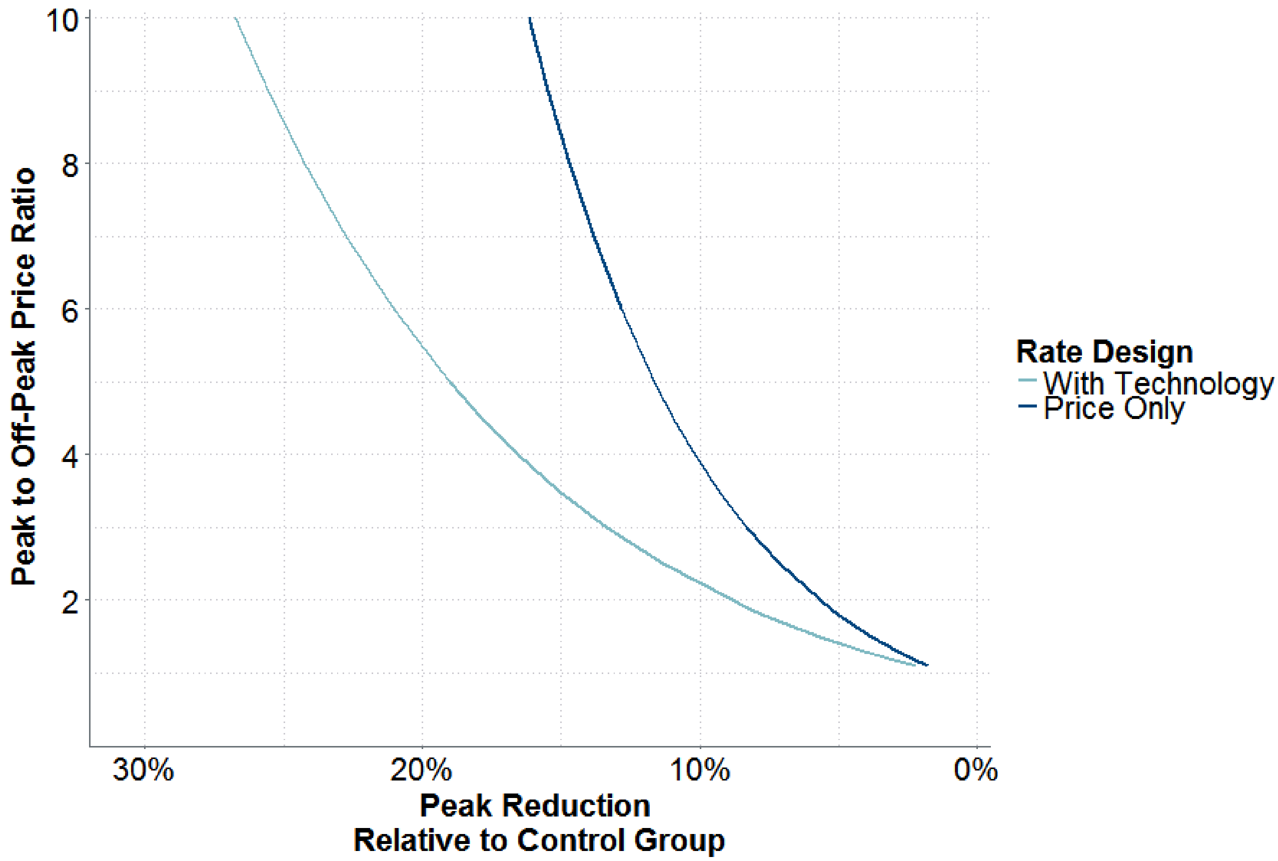
Martin Maechler, Peter Rousseeuw, Christophe Croux, Valentin Todorov, Andreas Ruckstuhl, Matias Salibian-Barrera, Tobias Verbeke, Manuel Koller, Eduardo L. T. Conceicao and Maria Anna di Palma, robustbase: Basic Robust Statistics R, package version 0.92-7, 2016, available: http://CRAN.R-project.org/package=robustbase out rate design. Indeed, the coefficients on the opt-out binaries in **Figure 13** demonstrate that opt-out designs have a positive impact of 3.9% on peak usage in comparison to opt-in designs. The coefficients on the log of the price ratio and the technology interaction term are still negative and significant under the alternative specification. This implies the treatment effect is robust even after adding additional control variables. Other specifications and controls were tested as well, including a binary if the duration of the peak period lasted more than four hours and a binary if the impacts were measured in the summer or in the winter. However, the coefficients were not significant. For this reason, they are not reported.

Figure 13: Alternative Regression Results

	Dependent variable:	
	Peak Impact	
	(1)	(2)
Log of Peak/Off-Peak Ratio	-0.065^{***}	-0.058^{***}
	(0.007)	(0.007)
Log of Peak/Off-Peak Ratio x Technology	-0.046^{***}	-0.047^{***}
	(0.008)	(0.008)
Opt-Out Binary		0.039^{***}
		(0.009)
Constant	-0.011	-0.028^{***}
	(0.007)	(0.009)
Observations	335	335
R^2	0.569	0.588
Adjusted R^2	0.566	0.584
Residual Std. Error	0.064 (df = 332)	0.063 (df = 331)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Using the estimated coefficients in **Figure 12**, **Figure 14** plots estimated % reductions in peak demand (i.e., demand response), against the peak to off-peak price ratios. The relationship between the price ratio and the % peak reduction has an arc-like shape, which has let us name the database Arcturus.

Figure 14: The Arc of Price Responsiveness



The Arc of Price Responsiveness shows that, on average, a customer facing a peak-to-off-peak price ratio of 2:1 will drop his or her demand by 5% and consume 95% of his or her typical peak usage. As this ratio increases to 4:1, the customer will consume 90% of his or her typical peak usage. The "With Enabling Technology" line in **Figure 14** shows that in the presence of enabling technology this effect is even stronger. At a ratio of 2:1, a customer with enabling technology will consume 91% of his or her typical peak usage, and he or she will consume 84% as the ratio increases to 4:1. The arc-like shape of the curve suggests additional increases in the peak-to-off-peak price ratio result in smaller changes to peak-shifting behavior.

Conclusion

The third wave of studies with time-varying rates has greatly expanded the body of evidence on residential customers' load-shifting behaviors. Arcturus 2.0 allows us to carry out a meta-analysis of the results from 63 pilots containing a total of 337 pricing treatments in nine countries located on four continents. We have shown beyond the shadow of a doubt that customers do reduce their peak load in response to higher peak to off-peak price ratios. Price-based demand response is real and predictable. It can be relied upon by utilities, regulators, independent system operators and other market participants to plan their activities. The magnitude of demand response is even stronger when the customer is provided with enabling technology such as smart thermostats and in-home displays. We expect the next wave of pilots might include other types of rate designs that combine time-varying rates with demand charges, demand subscription service, and transactive energy featuring peer-to-peer transactions. It is our intention to include the results of those studies in Arcturus 3.0.

Bibliography

AEFI Consulting Consortium, "Smart Grid, Smart City: Shaping Australia's Energy Future, National Cost Benefit Assessment," July 2014.

Faruqui, Ahmad and J. Robert Malko, "The residential demand for electricity by time-of-use: A survey of twelve experiments with peak load pricing," *Energy* 8:10, 1983, pp 781-795.

Faruqui, Ahmad, Hung-po Chao, Vic Niemeyer, Jeremy Platt, and Karl Stahlkopf, "Analyzing California's Power Crisis," *The Energy Journal* 22:4, 2001, pp 29–52.

Faruqui, Ahmad, William D. Bandt, Tom Campbell, Carl Danner, Harold Demsetz, 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 Manifesto on the California Electricity Crisis," May 2003.

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

Faruqui, Ahmad and Jackalyne Pfannenstiel, "California: Mandating Demand Response," *Public Utilities Fortnightly*, January 2008, pp. 48-53, available: http://www.fortnightly.com/display_pdf.cfm?id=01012008_MandatingDemandResponse.pdf.

Faruqui, Ahmad and Sanem Sergici, "Dynamic pricing of electricity in the mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment," *Journal of Regulatory Economics* 40:1, August 2011, pp. 82-109.

Faruqui, Ahmad and Jennifer Palmer, "Dynamic Pricing of Electricity and its Discontents," *Regulation* 34:3, Fall 2011, pp. 16-22, available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1956020.

Faruqui, Ahmad, Ryan Hledik, and Jennifer Palmer, *Time-Varying and Dynamic Rate Design*, Global Power Best Practice Series, The Regulatory Assistance Project (RAP), 2012.

Faruqui, Ahmad, Sanem Sergici, and Lamine Akaba, "Dynamic Pricing of Electricity for Residential Customers: The Evidence from Michigan," *Energy Efficiency* 6:3, August 2013, pp. 571–584.

Faruqui, Ahmad and Sanem Sergici, "Arcturus: International Evidence on Dynamic Pricing," *The Electricity Journal* 36:7, August/September 2013, pp. 55-65, available: http://www.sciencedirect.com/science/article/pii/S1040619013001656.

Faruqui, Ahmad, Sanem Sergici and Lamine Akaba, "Dynamic Pricing in a Moderate Climate: The Evidence from Connecticut," *The Energy Journal* 35:1, pp. 137-160, January 2014.

Faruqui, Ahmad, Ryan Hledik, and Neil Lessem, "Smart by Default," *Public Utilities Fortnightly*, August 2014, available: https://www.fortnightly.com/fortnightly/2014/08/smart-default.

Faruqui, Ahmad, Toby Brown and Lea Grausz, "Efficient Tariff Structures for Distribution Network Services," *Economic Analysis and Policy*, 2015, available: http://www.sciencedirect.com/science/article/pii/S0313592615300552.

Faruqui, Ahmad, Wade Davis, Josephine Duh, and Cody Warner, "Curating the Future of Rate Design for Residential Customers," *Electricity Daily*, 2016, available: https://www.electricitypolicy.com/Articles/curating-the-future-of-rate-design-for-residential-customers.

Faruqui, Ahmad, Neil Lessem and Sanem Sergici "Dynamic pricing works in a hot, humid climate: evidence from Florida," *Public Utilities Fortnightly*, May 2017, available: https://www.fortnightly.com/fortnightly/2017/05/dynamic-pricing-works-hot-humid-climate.

Faruqui, Ahmad and Henna Trewn, "Rethinking Customer Research in the Utility Industry," *Public Utilities Fortnightly*, July 2017, available: https://www.fortnightly.com/fortnightly/2017/07/rethinking-customer-research.

Faruqui, Ahmad and Henna Trewn, "Enhancing Customer-Centricity," *Public Utilities Fortnightly*, August 2017, available: https://www.fortnightly.com/fortnightly/2017/08/enhancing-customer-centricity.

Faruqui, Ahmad and Mariko Geronimo Aydin, "Moving Forward with Electric Tariff Reform," *Regulation*, Fall 2017, available: https://object.cato.org/sites/cato.org/files/serials/files/regulation/2017/9/regulation-v40n3-5.pdf.

Faruqui, Ahmad, "Innovations in Pricing," *Electric Perspectives*, September/October 2017, available: https://mydigimag.rrd.com/publication/?i=435343&ver=html5&p=42#{"page":42,"issue_id":435343}

Gouin, Andre and Craig Williamson, "SmartGridCity Pricing Pilot Program: Impact Evaluation Results, 2011 – 2013," prepared for Xcel Energy, December 6, 2013, available: http://s3.amazonaws.com/dive_static/diveimages/SGC_Pricing_Pilot_Evaluation_Report_FINAL-1.pdf.

Itron, Inc., "2016 Impact Evaluation of San Diego Gas & Electric's Residential Peak Time Rebate and Small Customer Technology Deployment Programs," March 20, 2017, available: http://www.calmac.org/publications/SDGE_PTR_2016_Final_Report.pdf.

Lessem, Neil, Ahmad Faruqui, Sanem Sergici, and Dean Mountain, "The Impact of Time-of-Use Rates in Ontario," *Public Utilities Fortnightly*, February 2017, available: https://www.fortnightly.com/fortnightly/2017/02/impact-time-use-rates-ontario.

Martin Maechler, Peter Rousseeuw, Christophe Croux, Valentin Todorov, Andreas Ruckstuhl, Matias Salibian-Barrera, Tobias Verbeke, Manuel Koller, Eduardo L. T. Conceicao and Maria Anna di Palma, robustbase: Basic Robust Statistics R, package version 0.92-7, 2016, available: http://CRAN.R-project.org/package=robustbase

Potter, Jennifer M., Stephen S. George, and Lupe R. Jimenez, "SmartPricing Options Final Evaluation," prepared for U.S. Department of Energy, September 5, 2014, available: https://www.smartgrid.gov/files/SMUD_SmartPricingOptionPilotEvaluationFinalCombo11_5_2014.pdf

Presented by Walter Graterri and Simone Maggiore, "Impact of a Mandatory Time-of-Use Tariff on the Residential Customers in Italy," Ricerca Sisterna Energetico, November 14-16, 2012, available: http://www.ieadsm.org/wp/files/Content/14.Espoo_IEA_DSM_Espoo2012_SimoneMaggiore_RSE.pdf

Yohai, Victor J., "High Breakdown-Point and High Efficiency Robust Estimates for Regression," *The Annals of Statistics* 15:20, 1987, pp. 642-656, available: https://projecteuclid.org/download/pdf_1/euclid.aos/1176350366

Appendix A: List of Pilots Included in the Arcturus Database

	Utility, Municipality, or Pilot	Year(s) of Study	Type of Rate	Country	U.S. State
[1]	Automated Demand Response Sytem Pilot	2004 - 2005	TOU, CPP	United States	CA
[2]	Ameren Missouri	2004 - 2005	CPP	United States	MO
[3]	Anaheim Public Utilities	2005	PTR	United States	CA
[4]	Ausgrid	2006 - 2008	TOU, CPP	Australia	-
[5]	Baltimore Gas & Electric Company	2008 - 2011	CPP, PTR	United States	MD
[6]	BC Hydro	2008	TOU, CPP	Canada	-
[7]	British Gas; Northern Powergrid	2012 - 2013	TOU	United Kingdom	-
[8]	California Statewide Pricing Pilot	2004 - 2005	TOU, CPP	United States	CA
[9]	City of Fort Collins	2015	TOU	United States	CO
[10]	City of Kitakyushu	2012 - 2013	CPP, VPP	Japan	-
[11]	City of Kyoto	2012 - 2014	CPP	Japan	-
[12]	Commonwealth Edison Company	2011, 2015	TOU, CPP, PTR	United States	IL
[13]	Connecticut Light & Power Company	2009	TOU, CPP, PTR	United States	CT
[14]	Consumers Energy	2010	CPP, PTR	United States	MI
[15]	Country Energy	2005	CPP	Australia	-
[16]	Department of Public Utilities in Los Alamos County	2013	CPP, PTR	United States	NM
[17]	Detroit Edison Company	2013	CPP	United States	MI
[18]	EDF Energy; E.ON; Scottish Power; Southern Energy	2007 - 2010	TOU	United Kingdom	-
[19]	Energex; Ergon	2011 - 2013	CPP	Australia	-
[20]	FirstEnergy Corporation	2012 - 2014	PTR	United States	OH
[21]	Florida Power & Light Company	2011	CPP	United States	FL
[22]	GPU, Inc.	1997	TOU	United States	NJ
[23]	Green Mountain Power	2012 - 2013	CPP, PTR	United States	VT
[24]	Gulf Power Company	2000 - 2002	TOU, CPP	United States	FL
[25]	Hydro One Limited	2007	TOU	Canada	-
[26]	Hydro Ottawa	2007	TOU, CPP, PTR	Canada	-
[27]	Idaho Power Company	2006	TOU, CPP	United States	ID
[28]	Integral Enegy	2007 - 2008	CPP	Australia	-
[29]	Ireland	2010	TOU	Ireland	-
[30]	Italy	2010 - 2012	TOU	Italy	-
[31]	Kansas City Power and Light Company	2012 - 2014	TOU	United States	KS/MO
[32]	Marblehead Municipal Electric Light Department	2011 - 2012	CPP	United States	MA
[33]	Mercury NZ	2008	TOU	New Zealand	-
[34]	Newmarket - Tay Power Distribution Limited	2009	TOU	Canada	-
[35]	Newmarket Hydro	2007	TOU, CPP	Canada	-
[36]	Northern Ireland	2003 - 2004	TOU	United Kingdom	-
[37]	NV Energy	2013 - 2015	TOU, CPP	United States	NV
[38]	Oklahoma Gas & Electric Energy Corporation	2011	TOU, VPP	United States	OK
[39]	Olympic Peninsula Project	2007	CPP	United States	WA/OR
[40]	Ontario Power Authority	2012 - 2014	TOU	Canada	-
[41]	Pacific Gas & Electric Company	2009 - 2016	TOU, CPP	United States	CA
[42]	PacifiCorp	2002 - 2005	TOU	United States	OR
[43]	PECO	2014	TOU	United States	PA
[44]	Portland General Electric	2002 - 2003, 2011 - 2013	TOU, CPP	United States	OR
[45]	Potomac Electric Power Company	2010	CPP, PTR	United States	DC
[46]	PSE&G	2006 - 2007	TOU, CPP	United States	NJ
[47]	Puget Sound Energy	2001	TOU	United States	WA
[48]	Sacramento Municipal Utility District	2011 - 2013	TOU, CPP	United States	CA
[49]	Salt River Project	2008 - 2009	TOU	United States	AZ
[50]	San Diego Gas & Electric Company	2011, 2015 - 2016	TOU, CPP, PTR	United States	CA
[51]	SmartGrid SmartCity Pilot	2012 - 2014	CPP	Australia	-
[52]	Southern California Edison Company	2016	TOU	United States	CA
[53]	Southwestern Ontario	2011 - 2012	TOU	Canada	-
[54]	Sun Valley Electric Supply Company	2011	CPP	United States	ND
[55]	UK Power Networks	2013	TOU	United Kingdom	-
[56]	Vermont Electric Cooperative	2013-2014	VPP	United States	VT
[57]	Xcel Energy, Inc.	2011 - 2013	TOU, CPP, PTR	United States	CO

Notes:
The results of one time-varying pilot are not public, so it is excluded in the above table but still included in Arcturus 2.0.
Some utilities have tested multiple pilots that report separate results. These pilots include:

- City of Kitakyushu (Kato et al. study; Ito et al. study);
- Commonwealth Edison Company (2011 TOU, CPP, PTR study; 2015 PTR study);
- Portland General Electric (2002 TOU Pilot; 2011 CPP Pilot);
- San Diego Gas & Electric (Residential Peak Time Rebate and Small Customer Technology Deployment Program, Voluntary Residential CPP and TOU Rates);
- SMUD (Residential Summer Solutions; Smart Pricing Options Pilot).

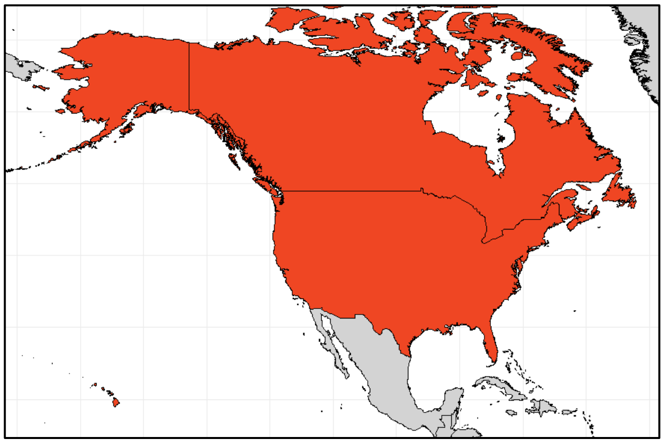
Including the pilots noted above brings the total count to 63 pilots.

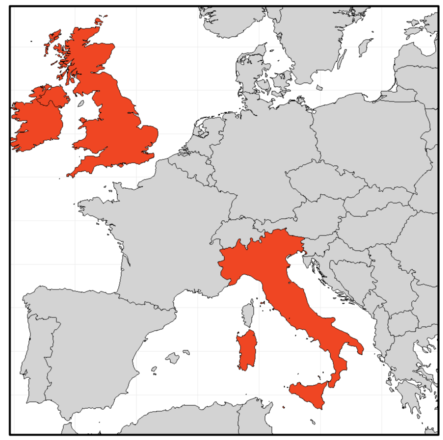
Appendix B: Peak Period Duration and Season of Pilots in Arcturus 2.0

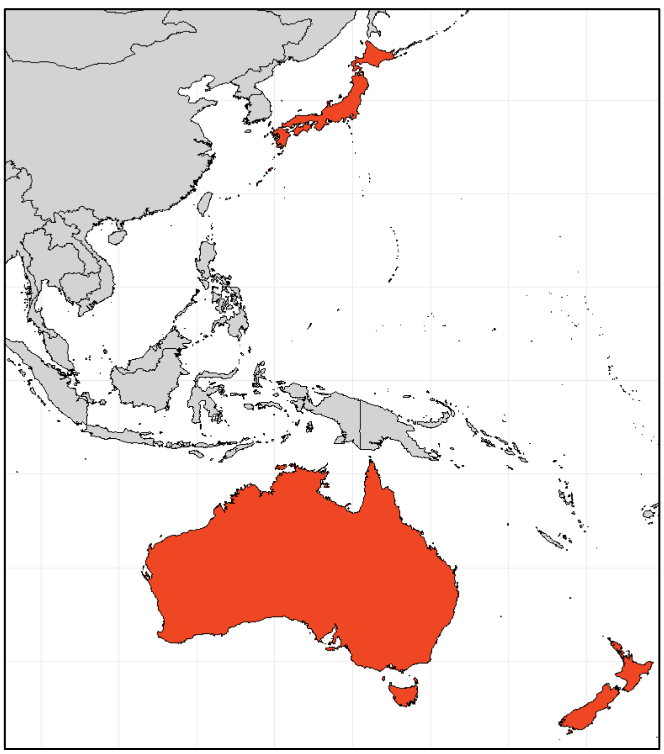
	Utility or Municipality	Average Peak Duration (Hours)	Seasons Included in Pilot		
			Summer	Winter	Annual
[1]	Automated Demand Response Sytem Pilot	5	No	No	Yes
[2]	Ameren Missouri	4	Yes	No	No
[3]	Anaheim Public Utilities	6	Yes	No	No
[4]	Ausgrid	4	Yes	Yes	Yes
[5]	Baltimore Gas & Electric Company	5	Yes	No	No
[6]	BC Hydro	6	No	Yes	No
[7]	British Gas; Northern Powergrid	4	No	No	Yes
[8]	California Statewide Pricing Pilot	5	Yes	No	Yes
[9]	City of Fort Collins	0	Yes	No	No
[10]	City of Kitakyushu	4	Yes	No	No
[11]	City of Kyoto	4	No	No	Yes
[12]	Commonwealth Edison Company	4	Yes	No	No
[13]	Connecticut Light & Power Company	5	Yes	No	No
[14]	Consumers Energy	4	Yes	No	No
[15]	Country Energy	2	No	No	Yes
[16]	Department of Public Utilities in Los Alamos County	3	Yes	No	No
[17]	Detroit Edison Company	4	Yes	No	No
[18]	EDF Energy; E.ON; Scottish Power; Southern Energy	3	No	No	Yes
[19]	Energex; Ergon	4	No	No	Yes
[20]	FirstEnergy Corporation	4	Yes	No	No
[21]	Florida Power & Light Company	4	No	No	Yes
[22]	GPU, Inc.	3	Yes	No	No
[23]	Green Mountain Power	5	Yes	No	Yes
[24]	Gulf Power Company	9	Yes	No	No
[25]	Hydro One Limited	6	Yes	No	No
[26]	Hydro Ottawa	7	Yes	Yes	Yes
[27]	Idaho Power Company	6	Yes	No	No
[28]	Integral Enegy	4	No	No	Yes
[29]	Ireland	2	No	No	Yes
[30]	Italy	11	No	No	Yes
[31]	Kansas City Power and Light Company	4	Yes	No	No
[32]	Marblehead Municipal Electric Light Department	6	Yes	No	No
[33]	Mercury NZ	12	No	Yes	No
[34]	Newmarket - Tay Power Distribution Limited	6	No	No	Yes
[35]	Newmarket Hydro	5	Yes	No	Yes
[36]	Northern Ireland	-	No	No	Yes
[37]	NV Energy	5	Yes	No	No
[38]	Oklahoma Gas & Electric Energy Corporation	5	Yes	No	No
[39]	Olympic Peninsula Project	4	No	No	Yes
[40]	Ontario Power Authority	6	Yes	Yes	No
[41]	Pacific Gas & Electric Company	5	Yes	Yes	Yes
[42]	PacifiCorp	6	Yes	Yes	No
[43]	PECO	4	Yes	No	No
[44]	Portland General Electric	6	Yes	Yes	No
[45]	Potomac Electric Power Company	4	Yes	No	No
[46]	PSE&G	5	Yes	No	Yes
[47]	Puget Sound Energy	-	No	No	Yes
[48]	Sacramento Municipal Utility District	3	Yes	No	No
[49]	Salt River Project	3	Yes	No	No
[50]	San Diego Gas & Electric Company	6	Yes	No	No
[51]	SmartGrid SmartCity Pilot	3	No	No	Yes
[52]	Southern California Edison Company	5	Yes	No	No
[53]	Southwestern Ontario	6	No	No	Yes
[54]	Sun Valley Electric Supply Company	4	Yes	No	No
[55]	UK Power Networks	6	No	No	Yes
[56]	Vermont Electric Cooperative	5	Yes	Yes	Yes
[57]	Xcel Energy, Inc.	6	Yes	Yes	No

Notes:
Pilots report customer impacts either during the summer months, winter months, or for the entire year. In some cases, pilots report all three. The corresponding columns in Appendix B have a value of “Yes” if any of the pilot’s experimental pricing treatments reported impacts for that corresponding season.

Appendix C: Maps of Countries included in Arcturus 2.0







Note: For confidentiality, one Asian utility is not included in the above map.