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Topics in Residential Electric Demand Response

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Abstract

Demand response and dynamic pricing are touted as ways to empower consumers, save consumers money, and capitalize on the "smart grid" and expensive advanced meter infrastructure. In this work, I attempt to show that demand response and dynamic pricing are more nuanced. Dynamic pricing is very appealing in theory but the reality of it is less clear. Customers do not always respond to prices. Price differentials are not always large enough for customers to save money. Quantifying energy that was not used is difficult.

In chapter 2, I go into more detail on the potential benefits of demand response. I include a literature review of residential dynamic pilots and tariffs to see if there is evidence that consumers respond to dynamic rates, and assess the conditions that lead to a response.

Chapter 3 explores equity issues with dynamic pricing. Flat rates have an inherent cross-subsidy built in because more peaky customers (who use proportionally more power when marginal price is high) and less peaky customers pay the same rates, regardless of the cost they impose on the system. A switch to dynamic pricing would remove this cross subsidy and have a significant distributional impact. I analyze this distributional impact under different levels of elasticity and capacity savings.

Chapter 4 is an econometric analysis of the Commonwealth Edison RTP tariff. I show that it is extremely difficult to find the small signal of consumer response to price in all of the noise of everyday residential electricity usage.

Chapter 5 looks at methods for forecasting, measuring, and verifying demand response in direct load control of air-conditioners. Forecasting is important for system planning. Measurement and verification are necessary to ensure that payments are fair. I have developed a new, censored regression based model for forecasting the available direct load control resource. This forecast can be used for measurement and verification to determine AC load in the counterfactual where DLC is not applied. This method is more accurate than the typical moving averages used by most ISO's, and is simple, easy, and cheap to implement.

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In memory of Lester.

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List of Abbreviations

AMI	Advanced meter infrastructure
CI	Confidence interval
ComEd	Commonwelath Edison
CPP	Critical-peak pricing
CPR	Critical-peak rebate
CTOU	Time-of-use & critical-peak pricing
DLC	Direct load control
DR	Demand response
ESPP	Energy Smart Pricing Plan
FERC	Federal Energy Regulatory Commission
FR	Flat-rate
HP	Hourly-pricing
kW	Kilowatt
kWh	Kilowatt hour
LIHEAP	Low income home energy assistance program
LMP	Locational marginal price
MF	Multi-family
MFH	Multi-family with electric space heat
MW	Megawatt
NERC	North American Electric Reliability Corporation
NETL	National Energy Technology Laboratory

OLS	Ordinary least squares regression
PG&E	Pacific Gas and Electric
PR	Peak rebate
PSE	Puget Sound Energy
PSE&G	Public Service Electric & Gas
RRTP	Residential real-time pricing
RSVP	Select Program Residential Service Variable Pricing
RTP	Real-time pricing
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SE	Standard error
SF	Single family
SFH	Single family with electric space-heat
SPP	California Statewide Pricing Pilot
TOU	Time-of-use pricing

Chapter 1

Introduction

The current US electric power system, with a few exceptions, addresses its problems on the generation side of the meter. Generators are expected to provide reliable service under virtually all circumstances, while those on the demand side of the meter can use as much power as they like, whenever they like, without regard for the state and cost of the supply. In addition to meeting the energy needs, the supply side almost exclusively provides ancillary services including capacity, balancing and regulation.

Most residential electricity consumers are permitted to use electricity without regard to extraordinary costs they may be imposing on the system. Residential customers pay the same flat rate when the wholesale price of power is -$50/MWh and when it is $2,500/MWh. Load profiles are becoming more peaky because residential customers have neither a signal nor an incentive to use less power during peak hours when the cost of generation is higher. In 2006 for example, 15% of generating capacity in PJM was used less than 1.1% of the time (Spees and Lave, 2007) and 15% of generating capacity in ISO-NE was used less than 0.9% of the time (Spees and Lave, 2008). Reductions in peak demand, could reduce the need for peak generators and lower system costs.

In restructured electricity markets, all generators are paid the same market clearing price, instead of their average cost, making incremental increases in demand substantially add to wholesale prices. Since most residential customer pay a flat-rate, they have no information on when to reduce their demand.

This work focuses on demand response (DR): methods to alter electricity consumption in order to maintain grid reliability or provide electrical service at a lower cost. I focus on two types of demand response: dynamic pricing and direct load control.

Demand response has been around for a long time. In 1934 Detroit Edison started using water heaters to manage load (Fanney and Dougherty, 1996). Demand response and energy efficiency programs became more popular in the 1970s in response to increased fuel prices and growing demand for electricity. The federal government reaffirmed the importance of demand response when Congress passed the Energy Policy Act of 2005:

> It is the policy of the United States that time-based pricing and other forms of demand response, whereby electricity customers are provided with electricity price signals and the ability to benefit by responding to them, shall be encouraged, the deployment of such technology and devices that enable electricity customers to participate in such pricing and demand response systems shall be facilitated, and unnecessary barriers to demand response participation in energy, capacity and ancillary service markets shall be eliminated.

The North American Electric Reliability Corporation[1] (NERC) considers DR to be an integral component of a reliable resource portfolio for the North American grid over the next decade. It is part of the solution for short term capacity shortfalls. NERC wide, DR resources have grown significantly and are projected

[1] A regulatory authority that assesses the reliability of the bulk power system in the continental US, most of Canada and parts of Mexico.

to continue growing over the next decade. Dispatchable[2] and controllable[3] DR grew from 30 GW in 2010 to 43 GW in 2011 and is projected to be 50 GW in 2021. Energy efficiency is projected to contribute an additional 5 GW by 2021 for a total DR contribution of 55 GW or 4.5% of the on peak resource portfolio. This is equivalent to offsetting approximately 4 years of peak demand growth. Figure 1.1 shows how DR is projected to reduce peak summer load until 2021 broken down by distpachable and controllable load, and energy efficiency. Figure 1.2 shows the projected dispatchable and controllable DR resource broken down by direct load control[4] (DLC), curtailable load[5], and load as a capacity resource[6] (NERC, 2011).

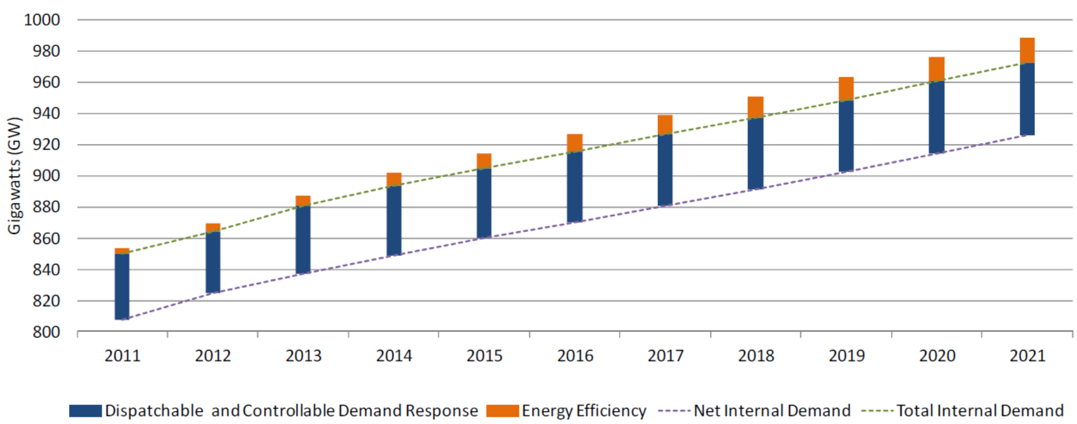

Figure 1.1: NERC wide on-peak summer demand projections with demand side management reductions (NERC, 2011).

[2]Demand-side resource curtailed according to instruction from a control center (NERC, 2011).

[3]Dispatchable, demand-side resources used to supplement generation resources resolving system and/or local capacity constraints (NERC, 2011).

[4]Demand-side management that is under the direct control of the system operator (NERC, 2011).

[5]Dispatchable, controllable, demand-side management achieved by a customer reducing its load upon notification from a control center. The interruption must be mandatory at times of system emergency (NERC, 2011).

[6]Demand-side resources that commit to pre-specified load reductions when system contingencies arise (NERC, 2011).

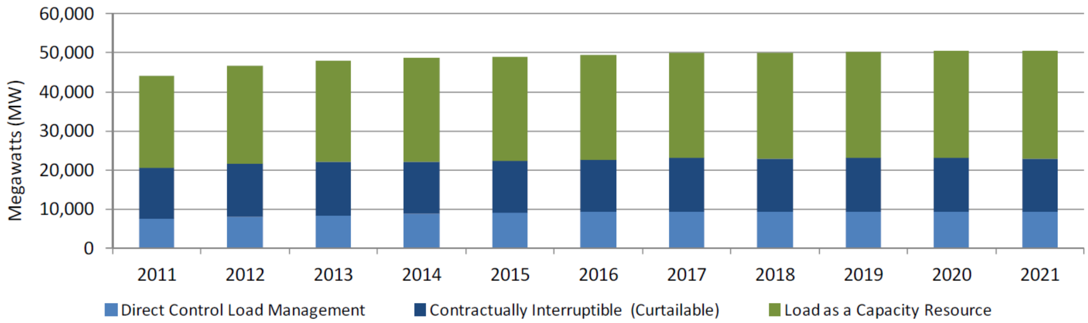

Figure 1.2: NERC-wide on-peak dispatchable and controllable demand response projections. (NERC, 2011).

Wholesale energy prices in restructured electricity markets change in real-time to reflect the real-time marginal cost of electricity. Residential electricity customers typically pay a retail rate that is decoupled from the real-time marginal wholesale rate. Most customers pay a flat-rate (FR) that is a load weighted average of price over an extended period of time (several months to several years). Flat rates create economic inefficiencies because customers have no signal to consume only the power that they value up to marginal cost.

Dynamic pricing exposes consumers to marginal price or to an approximation of it. Under real-time pricing (RTP) consumers pay the actual wholesale price for power. Under hourly-pricing (HP), consumers pay an hourly approximation of the real-time wholesale price, usually the day-ahead market value. Time-of-use pricing (TOU) is an approximation of RTP where the day, week or year is divided in several time periods, usually peak and off-peak (sometimes mid-peak or other periods are added in) and wholesale prices are averaged for each sub-division to that consumers always pay the same price during each time period. Critical-peak pricing (CPP) specifies one "critical" time period when price is dramatically higher than average price. The critical price is set in advance, however the critical time periods are usually specified only up to 24 hours in advance, based on anticipated grid conditions and price. CPP is sometimes applied in addition to TOU.

Another method of residential demand response, that does not involve pricing, is direct load control (DLC). Customers who enroll in DLC are usually paid a flat fee for the year and give their utility the option to cycle a discretionary load (usually an air-conditioner) when necessary. There are sometimes restrictions for the length of time of each cycling event and the total number of cycling events allowed over the course of a year.

There is substantial literature about demand response in electricity markets. Borenstein et al. (2002) give an overview of the economic theory (effect on efficiency and competitiveness) of demand side price incentives including interruptible contracts, paying customers to reduce demand, and dynamic pricing. They also describe issues in implementing time varying pricing and metering technology. Walawalkar et al. (2008) compare the social welfare gains to subsidies paid to price responsive demand and find that the value of the welfare gains exceed the value of the subsidies. Spees and Lave (2007) discuss the potential benefits of demand response and compare various methods of demand response including conservation, efficiency standards, economic load response, and dynamic pricing.

A report by LBNL (2006) describes the benefits of demand response, including financial reliability and market performance benefits. It found that there is little consistency in how demand response is quantified and recommend improving demand response analysis and measurement/verification so that DR policymakers can ensure that it is being implemented in an effective and efficient manner. Braithwait and Eakin (2002) discuss how DR can be part of power market design including dynamic pricing and interruptible and voluntary load reductions. Rahimi and Ipakchi (2010) give an overview of DR under the smart grid paradigm. Moslehi and Kumar (2010) and Kirby (2006) discuss the effects of DR on grid reliability.

Motegi et al. (2007) outline control strategies for DR response in the commercial sector for CPP and other peak reductions programs. Coughlin et al. (2008) address issues in measurement and verification of DR in the commercial sector.

Strbac (2008) assesses the benefits of DR in the UK including: aging assets, growth in renewable, transmission, distribution, security, and reliability. He also looks at the challenges including diversity of load, lack of metering, communication infrastructure, and increase in system complexity. Torriti et al. (2010) write about the DR experience in Europe. They discuss industrial, commercial, and residential programs and compare policies across Europe.

Here I further the literature by focusing on several important issues in the residential sector in the United States.

Demand response and dynamic pricing are suggested as ways to empower consumers, save consumers money, and capitalize on the "smart grid" and expensive advanced meter infrastructure (AMI). In this work, I show that demand response and dynamic pricing are more nuanced. Dynamic pricing is very appealing in theory, but the reality is less clear. Customers do not always respond to prices. Price differentials are not always large enough for customers to save money.

Exposing consumers to dynamic prices, should in theory, change consumer behavior when compared to flat-rate pricing. The reality of consumer response however, is unclear. Responding to prices that are constantly changing requires understanding electricity consumption, feedback on usage, information on prices, the potential to save money, and effort. In many regions price changes are small – a doubling of electric supply marginal price from 5¢/kWh to 10¢/kWh may only represent a 50% increase in total price, since there are many other costs (transmission, distribution, fixed connection fee, capacity, etc.). This price change may be in the satisficing dead-band for many consumers - i.e. there is no practical difference across a range from 5 to 10¢/kWh.

In chapter 2, I go into more detail on the potential benefits of demand response. I include a literature review of residential dynamic pilots and tariffs to see if there is evidence that consumers respond to dynamic rates, and assess the conditions that lead to a response. The literature shows that customers do respond somewhat to dynamic pricing, though most of the pilots and tariffs are biased, so it is difficult determine the real impact of dynamic pricing programs.

Chapter 3 explores equity issues with dynamic pricing. Flat rates have an inherent cross-subsidy built in because more peaky customers (who use proportionally more power when marginal price is high) and less peaky customers pay the same rates, regardless of the cost they impose on the system. A switch to dynamic pricing would remove this cross subsidy and have a significant distributional impact. I analyze the distributional impact of real time pricing under different levels of elasticity and capacity savings. Policy makers who are considering a switch to dynamic pricing must consider not only economic efficiency, but equity effects as well.

Chapter 4 is an econometric analysis of the Commonwealth Edison RTP tariff. I show that it is extremely difficult to find the small signal of consumer response to price in all of the noise of every day residential electricity usage. I suggest several steps utilities can take to more effectively and accurately measure household response to price in dynamic tariffs.

Chapter 5, joint work with Brandon Mauch looks at methods for forecasting, measuring and verifying demand response in direct load control of air-conditioners. These issues are becoming increasingly important, as penetration levels of demand response increase. Forecasting is important for system planning and measurement and verification are necessary to ensure that payments are fair. Forecasting, measurement and verification are difficult because the quantity of power that was *not* used is measured, and We must reconstruct a counterfactual situation where they would have been used in order to measure curtailment. We have developed a new, censored regression based model for forecasting the available direct load control resource. This forecast can be used for measurement and verification to determine AC load in the counterfactual where DLC is not applied. This method is more accurate than the typical moving averages used by most ISO's, and is simple, easy and cheap to implement.

This work has two major implications for policy makers and system planners considering the implementation of demand response programs: the importance of rigorous analysis before implementing dynamic pricing programs, and the need to consider measurement and verification issues.

Chapters 2 and 3 emphasize the importance of analysis before implementation. Chapter 2 shows that customers usually react to dynamic pricing, but the magnitude and nature of the response is highly dependent on the design of the program as well as exogenous factors. Poor program design can be disastrous but a carefully analysis and tariff design can yield an effective program. I show in chapter 3 that changing the structure of electricity pricing will have significant distributional effects. If policy makers do not consider the impact of the distributional effects in addition to efficiency improvements when switching to dynamic rates there may be a customer backlash.

Chapters 4 and 5 show the need for proper attention to measurement and verification issues. In chapter 4 I show the difficulty of measuring a response to dynamic pricing without proper program design. It will be difficult for policy makers to justify implementing costly programs if the benefits cannot be properly quantified. Chapter 5 shows that with the proper data and model, forecasting, measurement and verification of direct load control can be substantially improved.

Chapter 2

Residential Demand Response: A Review

This chapter discusses the use of dynamic pricing, particularly real time pricing, as a way to provide cheaper, more reliable service by making use of customer incentives. Section 2.1 describes the major problems that dynamic pricing seeks to address. Section 2.1.1 explains how dynamic pricing can be used for demand response. A literature review – in section 2.2 – gives an overview of the lessons learned from the major residential dynamic pricing projects.

2.1 Background

The electricity industry was restructured in the mid 1990's in order to provide competition that would lead to lower prices. Until then, a utility enjoyed a geographic monopoly with prices and services regulated by a state public utility

*A version of this chapter was submitted to the National Energy Technology Laboratory (NETL) as "Residential Demand Response: A Review and Analysis" in November, 2009 by Shira Horowitz and Lester Lave.

commission and interstate transfers of electricity regulated by the Federal Energy Regulatory Commission (FERC). The monopoly structure had been developed and operated for over a century. Until the late 1970's, regulators and the public developed confidence, and even admiration, for the electricity system.

Congress and FERC understood that restructuring would bring large changes to the system. Many of these changes were not anticipated and some led to major problems, such as generators and energy traders finding ways to manipulate the electricity market in California in 2000, leading to unprecedented high prices. We focus on another problem created by restructuring.

The decoupling of wholesale and retail electricity prices has exacerbated an inefficient power system. For residential and small commercial customers, the electricity system attempts to meet all demands and solve all problems on the generation side of the meter; residential prices are constant and load serving entities try to give reliable service by having large amounts of capacity above that required to meet expected demand. Residential customers have neither a signal nor an incentive to use less power during peak hours when the cost of generation is higher. This has resulted in load profiles becoming increasingly peaky. In 2006 for example, 15% of generating capacity in PJM was used less than 1.1% of the time (Spees and Lave, 2008) and 15% of generating capacity in ISO-NE was used less than 0.9% of the time (Spees, 2008). Eliminating a small fraction of peak demand could reduce the number of peak generators, which will lower system costs and increase reliability.

Restructuring exacerbated this problem because all generators are paid the market clearing price, rather than their generation cost. This means that small additions to peak demand increase wholesale prices significantly. Since most customers paid a flat rate that is only indirectly related to the market clearing price, residential customers have no reason to lower their use during peak demand periods.

2.1.1 Dynamic tariffs

For markets selling gasoline, produce, beef, and other products, rising prices lead many consumers to search for substitute products, put off the purchase, or purchase less. Reducing peak demand requires sending both a signal and providing an incentive to customers to guide their behavior. Linking retail prices to wholesale prices through a dynamic pricing tariff accomplishes both, since the rising price is the signal and creates an incentive to consume less or use power when it is cheaper. In particular, the first watts of electricity are extremely valuable to a consumer, with subsequent watts bringing less value per kWh. Thus, higher prices should encourage customers to consume less when the cost of electricity exceeds the value they place on it.

The four main groups of dynamic tariffs are:

1. **Time-of-use pricing (TOU)**: TOU divides a day into two or three periods with different prices. The times and prices may change seasonally. The prices roughly approximate the cost of power during each period.

2. **Critical-peak pricing (CPP)**: CPP builds on time of use pricing by specifying a 'critical' time with a much higher price. Sometimes CPP is done in addition to TOU pricing. The CPP is invoked only when the system is under stress; the CPP appeal and the high price are signals to consumers to take greater steps to reduce demand.

3. **Real-time pricing (RTP)**: RTP provides the most accurate cost-price signal, since it reflects the wholesale market clearing price. RTP prices

typically change hourly, but can theoretically change in any increment that the market is cleared (typically 5 minutes or 15 minutes). Ideally RTP would reflect the real-time dynamic changes in wholesale prices; however in many cases, day ahead pricing is used to give customers a chance to plan their usage patterns.

4. **Peak rebate (PR):** Under PR schemes, customers receive rebates for energy they don't use during a specified time period. A baseline usage is assigned to each customer, usually based on an average of previous usage. During the specified time, if a customer uses less than his baseline, he receives a rebate for the difference in his baseline usage and usage during that time period. If he uses more than his baseline usage, there is usually no consequence. PR is usually applied to critical peak hours and is referred to as 'critical-peak rebate' (CPR). It can also be applied to peak hours under TOU.

If customers were able to react to electricity prices in real time by changing their load, the entire system would benefit. The high prices at peak demand would reduce use, requiring less generation capacity. The most expensive generation plants could be scrapped, or at least used less, lowering costs. There would be less of a threat of market power abuse in deregulated markets, since customers would curb their use when prices rose. If prices were sent out in 1-15 minute increments, load could be used as spinning reserve, making the entire system cheaper and more efficient, with benefits to all ratepayers.

2.1.2 Why demand response?

The current electricity system has been designed to provide reliable service to customers whatever their use. The systems works reasonably well, but is expensive and there are occasional reliability problem.

At times of peak demand, much of the electricity use is non critical in the sense that it could be shifted to some other time or simply curtailed. Many houses have some of the lights, plasma TVs, and other devices that are running because no one bothered to shut them off, even though they are providing no service. With some inconvenience, electric hot water heaters, dishwashers and washing machines could be run off peak; thermostats could be changed a few degrees to lower electricity use. In all these cases, without a signal that the electricity is in short supply, consumers are not even aware of the need to reduce use.

A system that was able to rely on demand side adjustment for regulation and large scale adjustment for short time periods by control of air conditioners, hot water heaters, swimming pool pumps, and other discretionary loads, would be a more robust and more efficient system. Running generators at less than full capacity so that they can adjust to load is inefficient and expensive.

Demand response has the potential to contribute a huge social welfare benefit. An analysis by Walawalkar et al. (2008) determined that if demand were reduced by 4% from 22.5 GW to 21.5 GW in the New England ISO, the short-run marginal cost of production would drop by 47% from $158/MWh to $84/MWh. Spees and Lave (2008) have shown (see figure 2.1) the potential for lowering the peak load of PJM as a function of price elasticity of demand.

Spees and Lave (2008) have shown that much of the benefit of demand side response can be realized with less than half the customers on a dynamic tariff. If the large customers that represent approximately half the total demand had

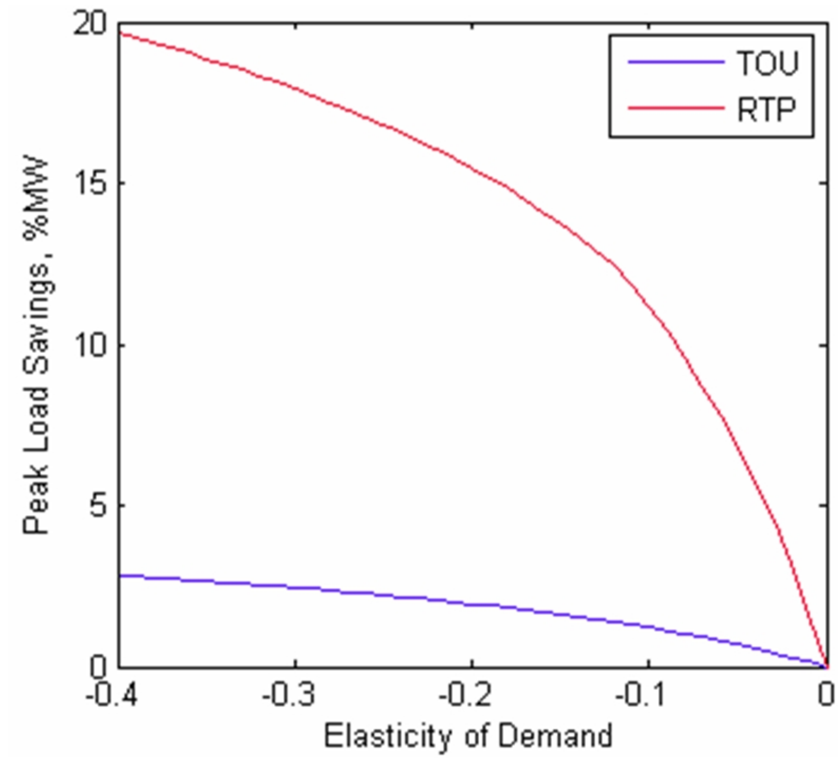

Figure 2.1: Peak load reduction in PJM (percent) under TOU and RTP as a function of price elasticity of demand (Spees and Lave, 2008).

smart meters and adjustment devices, virtually all the generation and transmission savings would be achieved, and virtually all the benefits of customer side regulation and eliminating spinning reserve would be realized. Almost all customers, whether they had a real time meter or not, would benefit. Those on dynamic tariffs who adjust their usage would benefit directly. The remaining customers would benefit from the lower costs due to the adjustment of those with the meters.

2.2 Literature review

Some utility executives doubt the ability of residential customers to understand and react to changing prices. Since the extent to which residential customers react to changing price is an empirical, not a theoretical question, dozens of experiments have been done to estimate customer reactions. In addition to the experiments, a number of utilities have tariffs that feature prices that change by time of day, that use critical peak pricing, and even some that have real time pricing of one sort or another. These tariffs show that residential customers can understand and respond to dynamic prices, but some executives don't consider the responses to be sufficiently "reliable."

This literature review focuses on the lessons learned from 8 residential TOU tariffs, 10 residential CPP tariffs and 3 residential RTP tariff. Comparing the results of these pilots requires care, since:

1. different populations were used, some random, others self selected,
2. the price differentials in each tariff are different,
3. some had representative control groups, others did not,
4. enabling automated technology was given to customers in some pilots, while other customers were left to respond by themselves, and
5. The climate and other factors affecting demand were different in each pilot (air conditioner penetration was different across pilots; etc.).

Nevertheless, we make comparisons to get a general idea of what is possible with dynamic tariffs.

A brief description of all of the reviewed tariffs is given in section 2.2.1. The programs are ordered by start date. Section 2.2.2 roughly compares the different programs.

A brief note on terminology: *Price Elasticity of Demand* is a way of measuring customer response to price. It is defined as the ratio of the percent change in quantity demanded to the percent change in price, mathematically expressed as:

$$E_d = \frac{\Delta Q/Q}{\Delta P/P}$$

Where Q is the quantity of electricity demanded and P is the price of electricity. $E_d = -0.10$ means that a 10% increase in price results in a 1% decrease in energy purchased.

Price Elasticity of Substitution measures the propensity of consumers to shift demand for power from peak times to off peak times. Mathematically expressed as:

$$E_s = \frac{\Delta(Q_1/Q_2)}{\Delta(P_1/P_2)} \frac{P_1/P_2}{Q_1/Q_2}$$

Where Q_t is the quantity of electricity demanded during time t when the price of electricity is P_t.

2.2.1 Description of dynamic pricing tariffs

GPU - CPP Pilot

Utility GPU.

Program Name CPP Pilot.

Location New Jersey.

Dates Summer 1997.

Tariff description There were two treatment groups that were subject to CPP tariffs and a control group that was on the standard residential tariff. Tariffs are shown in table 2.1.

Enabling Technology In house communication equipment.

Table 2.1: GPU TOU tariffs.

	Hours	Tariff (¢/kWh)	
		Group 1 - High	Group 2 - Low
Off-peak	Weekends Holidays Weekdays 1am-8am Weekdays 9pm-12pm	6.5	9
Shoulder	Weekdays 9am-2pm Weekdays 7pm-8pm	17.5	12.5
Peak	Weekdays 3pm-6pm	30	25
Critical	When called during peak	50	50

Notification Via in house communication equipment.

Elasticity of Substitution -0.30 based on constant elasticity of substitution model. Elasticities of substitution based on the generalized Leontief model are shown in table 2.2.

Table 2.2: Elasticities of substitution for GPU TOU pilot based on the generalized Leontief model.

Month	Time	High tariff	Low tariff
1	Peak–shoulder	-0.155	-0.166
	Peak–off-peak	-0.395	-0.356
	Shoulder–off-peak	-0.191	-0.187
2	Peak–shoulder	-0.055	-0.06
	Peak–off-peak	-0.407	-0.366
	Shoulder–off-peak	-0.178	-0.176

Average Reduction Table 2.3 shows average reduction during peak periods, relative to the control group. The treatment group used less energy every day compared to the control group, although this difference was not statistically significant.

Table 2.3: Average reduction of customers on the GPU TOU tariff during peak periods, relative to the control group.

	Peak hour	Demand reduction (kW)	Percent reduction
Non-critical days		0.53	26%
CPP days	1	1.24	50%
	2	1.00	40%
	3	0.59	24%

References Faruqui and Sergici (2009).

Gulf Power - Select Program RSVP

Utility Gulf Power.

Program Name Select Program Residential Service Variable Pricing (RSVP) – Permanent.

Location Florida.

Dates 2001 – Present.

Tariff description A three part TOU tariff with CPP is used. The rates from June 2002 – present are in table 2.4.

Table 2.4: Rates for RSVP program.

		Off-peak	Mid-peak	Peak	Critical Peak
Cost (¢/kWh)		1.785	3.021	7.598	28.500
Winter hours	Weekday	11pm-5am	5am-6am 10am-11pm	6am-10am	When called
	Weekend	11pm-6am	6am-11pm	n/a	
Summer hours	Weekday	11pm-6am	6am-1pm 6pm-11pm	1pm-6pm	When called
	Weekend	11pm-6am	6am-11pm	n/a	

Enabling Technology Programmable communicating smart thermostat which automatically reacts to critical events. The thermostat can be programmed from the internet. There is a gateway connected to the meter that allows other appliance to receive pricing information from the meter including pool pumps and water heaters.

Notification Via smart thermostat.

Average Reduction Average reductions from a 2002 evaluation are in table 2.5.

Table 2.5: Average reductions for the RSVP program from a 2002 evaluation.

Period	Demand reduction	Energy reduction
Peak	2.1 kW/h	22%
Critical Peak	2.75 kW/h	41%

References Faruqui and Sergici (2009); Gulf Power (2009).

Puget Sound Energy - TOU Program

Utility Puget Sound Energy (PSE).

Program Name TOU – permanent.

Location Seattle Suburbs.

Dates 2001 - 2002.

Tariff description TOU program for residential and small commercial customers. The peak price was approximately 15% higher than flat rate and off peak was 15% lower. In 2002 customers were charged an additional \$1/month to cover meter reading costs.

Participants 300,000 customers placed on program, with opt-out option.

Bill Savings In 2002, 94% of customers had a net increase in their bill. There was an average of \$0.20/month in energy savings, however due to the \$1/month meter reading charge, customers were paying \$0.80/month more on average.

Average Reduction 5% of total energy was reduced per month on average over 15 months.

Other The TOU program was cancelled due to customer dissatisfaction and negative media coverage.

References Faruqui and Sergici (2009).

California Statewide Pricing Pilot - CPP-F

Utility Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E).

Program Name California Statewide Pricing Pilot (SPP)– CPP-F.

Location California.

Dates 2003-2004.

Tariff description Critical peak pricing - fixed:

Fixed peak period 2 pm - 7 pm;

15 Critical days per year; Critical peak: 59¢/kWh;

Peak: 22¢/kWh;

Off peak: 9¢/kWh;

Control: 13¢/kWh.

Participants 542 (stratified sample, opt out design).

Notification Day ahead notification for critical days.

Expected Bill Savings The tariff was designed to be revenue neutral for the average customer with no behavior change, and not more than a 5% bill change for customers with non-average usage. It was designed for 10% savings for customers who shifted peak usage by 30%.

Elasticity of Demand 2003: $-.035$;

2004: -0.054.

Elasticity of Substitution 2003: -0.09;

2004: -0.086.

Average Reduction Average energy reductions during peak periods for both critical and non-critical days, across climate zones are shown in table 2.6.

Table 2.6: Average energy reduction during peak periods across climate zones in the SPP – CPP-F pilot.

	Mild climate zone	Statewide	Hottest climate zone
Critical days	7.6%	13.1%	15.8%
Non critical days	2.2%	4.7%	6.5%

Other

- The most responsive groups were: single family homes, smaller households bigger homes, college graduates, central AC.
- There was not a significant difference for those homes with higher than average energy use.
- Total energy usage remained almost the same – reductions during peak periods were offset by increases during off peak periods.

- There was more response during the summer than the winter, and during the winter than the spring or fall.

References Charles River Associates (2005).

California Statewide Pricing Pilot – CPP-V

Utility SDG&E.

Program Name California Statewide Pricing Pilot – CPP-V (SPP).

Location San Diego.

Dates 2003 and 2004.

Tariff description Two part TOU tariff with variable length peak period on critical days, which could be called on the day of the critical event.

Off-peak price: 10¢/kWh

Peak price: 24¢/kWh

Critical peak price: 65¢/kWh

Participants *Track A*: 125 households. 80% of participants had AC and the group as a whole had relatively high income.

Track C: 125 single family households, all with central AC.

Enabling Technology *Track A*: Participants were given the option of technology to control either their hot water heater, AC or pool pump.

Track C: All participants were given smart thermostats.

Expected Bill Savings The tariff was designed to be revenue neutral for the average customer with no behavior change, and not more than a 5% bill change for customers with non-average usage. It was designed for 10% savings for customers who shifted peak usage by 30%.

Elasticity of Demand *Track A*: -0.027;

Track C: -0.044.

Elasticity of Substitution Track A: -0.111;

Track C: -0.077.

Average Reduction Average energy reduction on critical peak days:

Track A: 16;%

Track C: 27.%

Other

- The populations from the two tracks are not comparable. Track C consisted entirely of single family homes with central AC, and had a higher mean income than Track A.
- The energy reduction during peak hours was equally offset by a 2% increase in usage during off-peak hours, resulting in no net conservation.
- In track A, the differences in usage between those with and without enabling technology are not statistically significant, so it is unclear if the technology had any effect.
- Two-thirds of the demand reduction of Track C is attributed to the enabling technology, and the rest to price induced behavioral change.

References Charles River Associates (2005).

California Statewide Pricing Pilot – TOU

Utility PG&E, SCE and SDG&E.

Program Name California Statewide Pricing Pilot (SPP) - TOU.

Location California.

Dates 2003 and 2004.

Tariff description Two part TOU tariff:

Peak price: 22¢/kWh;

Off-peak price: 10¢/kWh;

Control group price (flat rate): 13¢/kWh.

Participants 200, stratified sample, opt out design.

Expected Bill Savings Tariff was designed to be revenue neutral for the average customer with no behavior change, and not more than 5% change in bill for customers with non-average usage. It was designed for 10% savings for customers who shifted peak usage by 30%.

Elasticity of Demand Summer 2003: -0.117;

Summer 2004: -0.132.

Elasticity of Substitution Summer 2003: 0.099;

Summer 2004: 0.

Average Reduction 2003: -5.9%;

2004: 0.6%.

Other Due to the small sample size, many of the results were insignificant, however, if the results are accurate, they indicate that a modest price difference may result in behavior change. Since the price differentials were small, the reduction may have been due to awareness and education, not price.

References Charles River Associates (2005).

ComEd - Residential Real Time Pricing

Utility Commonwealth Edison (ComEd).

Program Name Energy Smart Pricing Plan (ESPP)/Residential Real Time Pricing (RRTP).

Location Illinois - Greater Chicago.

Dates 2003–2006: Pilot;

2007 – Present: Permanent.

Tariff description 2003–2006: Hourly day ahead prices;

2007–Present: real time pricing;

Price cap: 50¢/kWh;

During the pilot phase, participants received an access charge reduction of 1.4¢/kWh.

Participants Started with about 750 participants in 2003 (650 on RTP, 100 as a control group). As of April 2009 there were approximately 6,250 participants. Participants self select into the program by opting in. There was a control group in 2003 consisting of customers who chose to participate in the program, but were deferred for one year so they could serve as the control group.

Enabling Technology Beginning in 2004, some participants received switches to automatically cycle their AC's during high price periods.

In 2006 some participants received an 'energy orb' that changes color as price changes.

Notification Participants must call a toll free number or access a website to find out the next day's prices. From 2003–2006 participants paid day ahead prices, so the prices they looked up is what they actually paid. From 2007 and on, the prices listed are the day-ahead prices, however customers pay real-time prices, which may differ from day-ahead prices. Customers can access the real-time prices via a website or a browser plug-in.

When prices are above a certain threshold (10, 13 or 14 ¢/kWh depending on the year), customers receive an outgoing communication by email or phone.

Expected Bill Savings \$5 - \$25 per month. A plurality of customer saved about \$10/month. Customers who do not shift usage are still expected to save about 10% from the reduction in access charge.

Elasticity of Demand Shown in table 2.7.

Table 2.7: Elasticities of demand for ComEd RTP from 2003 - 2006. Note: Single-family refers to a single family home; multi-family refers to multi-family structures such as apartment buildings.

Year	Conditions	Elasticity of demand
2003	Price above 10¢/kWh	−0.042
2004	Price above 10¢/kWh	−0.080
2004	Single family, no AC	−0.080
	Single family, window AC	−0.080
	Single family, central AC	−0.052
2004	Multi family, no AC	−0.117
	Multi family, window AC	−0.105
	Multi family, central AC	−0.087
2005	Before 4 pm	−0.015
	High price days before 4 pm	−0.020
2005	After 4 pm	−0.026
	High price days after 4 pm	−0.048
	High price days for Central AC cycling	−0.069
2006	Below 13¢/kWh	−0.047
	Above 13¢/kWh	−0.082
2006	With energy orb	−0.067
	With central AC cycling	−0.098

Average Reduction 3% of total summer usage

Other

- The program is administered by CNT Energy, a community energy cooperative. Customers had to be cooperative members to participate in the program during the pilot phase.
- Older households with higher income were less likely to respond, while those with lower incomes in multi-family homes were more likely to respond.
- In general, those who self-selected into the program were more likely to have above average income, live in a single-family home, have internet access, have newer appliances, new insulation and smaller household size.
- The best response was from multi-family structures with no AC, showing there are loads that can be shifted other than AC.
- After several consecutive hours or days of high price, response fell off. In addition there was a 'saturation effect' where consumption increased in the third hour of consecutive high prices. This may be because air-conditioners whose thermostats have been raised reach their new, higher, set point at about this time.
- Participants reported changing energy usage by: changing AC usage and changing laundry washing times.
- According to surveys, participants were generally satisfied with the program. The greatest motivation for participation was to save money. Secondary benefits were: value of perceived control, ability to manage energy, environmental effects, understanding gained about energy usage and equipment received.

References Summit Blue (2004); Summit Blue (2005); Summit Blue (2006); Summit Blue (2007).

AmerenUE - Residential TOU Pilot Study

Utility AmerenUE.

Program Name Residential TOU Pilot Study.

Location St. Louis and St. Louis County, Missouri.

Dates 2004.

Tariff description There were three different treatment groups. During the winter all groups were on a 3 tier TOU tariff (see table 2.8). Different TOU prices and times apply during the summer, and treatment groups 2 and 3 have an additional CPP tariff (see table 2.9).

Treatment 1: 3 tier TOU.

Treatment 2: TOU + CPP. Same as treatment 1, but with the addition of a CPP time, which can be called 10 times during the summer during peak times.

Treatment 3: Same as treatment 2, but customers were given smart thermostat.

Customers received $25 for enrolling in the pilot, and $75 after six months.

Participants Treatment 1: 88 treatment group, 89 control;

Treatment 2: 85 treatment group, 89 control;

Treatment 3: 77 treatment group, 117 control.

Enabling Technology Smart thermostat for treatment group 3.

Notification Day ahead for CPP via automated phone call.

Table 2.8: Winter tariff for AmerenUE residential TOU pilot. This tariff applies to all three treatment groups during the winter.

	Time	Price(¢/kWh)
Off-peak	Weekends Holidays Weekdays 9pm-5am	3
Mid-peak	Weekdays 9am-4pm	5.3
Peak	Weekdays 5am-9am Weekdays 4pm-9pm	6.95

Table 2.9: Summer tariff description for AmerenUE residential TOU pilot.

		Price (¢/kWh)	
	Time	Treatment 1	Treatment 2/3
Off-peak	Weekends Holidays Weekdays 10pm-10am	4.8	4.8
Mid-peak	Weekdays 10am-3pm Weekdays 7pm-10pm	7.5	7.5
Peak	Weekdays 3pm-7am	18.31	16.75
Critical Peak	When called (up to 10 times)	n/a	30

Other An analysis of this data concluded that TOU was not effective – the difference between usage for the control and treatment groups on TOU was not statistically significant, without enabling technology. The CPP tariff motivated a small response during critical times only. Treatment group 3 (with enabling technology) used significantly less energy than the control group during critical peak and peak periods and shifted a statistically significant amount from peak times to mid-peak or off-peak periods.

References Puckett and Hennessy (2004) .

Anaheim Public Utilities - Critical Peak Pricing Experiment

Utility Anaheim Public Utilities.

Program Name Critical Peak Pricing Experiment (pilot).

Location Anaheim, CA.

Dates June – October 2005.

Tariff description Critical peak rebate: standard tariff except 12 pm to 6 pm on peak days when participants received a rebate of 35¢/kWh for reductions below their baseline. The baseline was calculated for each customer as the average of the three highest peak period consumption levels for weekdays during a trial period.

Participants 71 in treatment group;
52 in control group;
considered a random sample since recruitment letter did not mention choice to opt out.

Notification Day before peak event by telephone or email.

Average Reduction 12% below the control group during CPP events.

Other Customers had an incentive to increase usage on non-CPP days so that their baseline would be higher, and they would receive larger rebates on CPP days. In fact, on off peak weekdays, the treatment group had significantly higher consumption than the control group. Because of this, up to half of the reduction on CPP days may actually be due to increases in use on non-CPP days. The reduction of the treatment group relative to the control group was greater on hotter days.

References Wolak (2006).

Energy Australia - Network Tariff Reform

Utility Energy Australia.

Program Name Network Tariff Reform.

Location New South Wales, Australia.

Dates 2005 - present.

Tariff description Tested three tariffs: (1) seasonal (2) dynamic (3) information only.

Participants 650 residential customers in 2005.

Enabling Technology In home displays.

Notification Via in home displays, SMS, phone, email.

Elasticity of Demand Residential customers, 2006: -0.30 to -0.38 (summer); -0.47 (winter).

Elasticity of Substitution -0.30 to -0.38.

Maximum Reduction Peak usage reduced by 24% during high rates and 20% during medium rates.

References Faruqui and Sergici (2009).

Idaho Power Company - Energy Watch Program

Utility Idaho Power Company.

Program Name Energy Watch Program - CPP (pilot);

Time of Day Program - TOU (pilot).

Location Emmet and Letha, Idaho.

Dates 2005 - 2007.

Tariff description The CPP and TOU tariff only apply during June, July and August.

Energy Watch Program – CPP: Customers pay a flat rate except during events, where the rate increases by 20¢/kWh. Events occur from 5-9pm up to 10 days per summer.

Time of Day Program – TOU: 3 period TOU tariff, shown in table 2.10.

Table 2.10: Tariff description for Idaho Power Company Time of Day program.

	Time	Price (¢/kWh)
Off-peak	Weekends Holidays Weekdays 9pm-7am	4.5
Mid-peak	Weekdays 7am-1pm	6.1
Peak	Weekdays 1pm-9pm	8.3

Participants 58 - CPP.

Notification Phone and or email by 4 pm the day before.

Expected Bill Savings CPP, 2005: 10%;

TOU, 2005: 5% .

References Idaho Power (2008).

Olympic Peninsula Project

Utility Portland General Electric and BPA.

Program Name Olympic Peninsula Project.

Location Washington State.

Dates 2005-2006.

Tariff description Control group and three treatment groups:

1. Fixed price: 8.1¢/kWh at all times;
2. TOU/CPP: Peak and off peak periods, prices are shown in table 2.11, peak prices increased during critical event;
3. RTP: 5 minute real-time prices, participants pre-programmed appliances to respond to prices.

Table 2.11: TOU/CPP rates for Olympic Peninsula Project.

	Summer		Winter	
Period	Time	Charge (¢/kWh)	Time	Charge (¢/kWh)
Off-peak	9am-3pm	5	9am-6pm, 9pm-6am	4.119
Peak	3pm-9pm	13.5	6am-9pm, 6pm-9pm	12.15
Critical-peak	When called	35	Not called	n/a

Participants 112 participants, all with high speed internet, electric HVAC, electric water heating and electric clothes drying.

Enabling Technology Two way communicating, price responsive switches for major appliances.

Bill Savings Average monthly bill savings relative to control group:

Fixed price: 2%;

TOU/CPP: 30%;

RTP: 27%.

Average Reduction Change in average energy consumption compared to control group:

Fixed price: 4% increase;

TOU/CPP: 21% decrease;

RTP: No change.

Other Although there was no change in average energy consumption for the RTP group, it successfully reduced peak demand. TOU/CPP was most effective at reducing peak demand.

References Hammerstrom (2007).

Hydro Ottawa - Ontario Energy Board Smart Price Pilot

Utility Hydro Ottawa.

Program Name Ontario Energy Board Smart Price Pilot.

Location Ontario, Canada.

Dates August 1, 2006 – February 28, 2007.

Tariff description There were three tariffs tested: (1) TOU (2) CPP (3) Critical peak rebate (CPR). The TOU rates are summarized in table 2.12. The CPP rates are the same as those for TOU, but with the addition of a 30¢/kWH charge during critical peak events. Off-peak rates were reduced to 3.1¢/kWh for CPP customers. The CPR customers received a 30¢/kWh refund for the difference between actual and baseline usage during critical events. Baseline usage was calculated as the average usage during the same hours over the five previous non-event, non-holiday weekdays, multiplied by 1.25 for a weather adjustment.

Table 2.12: Tariff summary for Ontario Energy Board Smart Price Pilot

	Summer		Winter	
	Hours	Price (¢/kWH)	Hours	Price (¢/kWh)
Off-peak	Weekdays 10pm-7am Weekdends Holidays	3.5	Weekdays 10pm-7am Weekends Holidays	3.4
Mid-peak	Weekdays 7am-11am Weekdays 5pm-10pm	7.5	Weekdays 11am-5pm Weekdays 8pm-10pm	7.1
Peak	Weekdays 11am-5pm	10.5	Weekdays 7am-11am Weekdays 5pm-8pm	9.7

Participants TOU: 124;

CPP: 124;

CPR: 125;

Control: 125;

Overall response rate to recruitment letter: 25.5%.

Notification Critical peak notification by phone, email or SMS the day before.

Bill Savings 3% on average for TOU group.

Average Reduction Energy reductions are shown in table 2.13.

Table 2.13: Energy reduction by tariff for the Ontario Energy Board Smart Price Pilot.

	Percent reduction	
Group	On-peak period	CPP event
TOU	2.4%	Not significant
CPP	11.9%	25.4%
CPR	8.5%	17.5%

.

Other Customers expressed overall satisfaction with the pilot because: (1) increased awareness on how to reduce electricity bill; (2) additional control over electricity costs; (3) environmental benefits.

References Strapp et al. (2007)

PSE&G - myPower Sense & myPower Connection

Utility Public Service Electric & Gas (PSE&G)

Program Name myPower Sense (pilot - education only);

myPower Connection (pilot - CPP).

Location Cherry Hill and Hamilton Township, NJ.

Dates 2006-2007.

Tariff description The base rate was 9¢/kWh. TOU and CPP prices, shown in table 2.14, for myPower Connection are relative to the base rate. Prices differ for summer and non-summer months.

Table 2.14: Prices for myPower Connection. Prices are given as differences from the base rate. The base rate was 9¢/kWh, so a price difference of -5¢/kWh indicates that customers were paying 4¢/kWh.

		Price difference (¢/kWh)	
	Time	Summer	Non-summer
Night discount	10pm-9am	-5	-4
On peak adder	1pm-6pm	8	3
Critical peak adder	when called	68	23

Participants myPower Sense: 459;

myPower Connection: 377;

Control: 450;

Response rate to recruitment letter: 4%.

Enabling Technology Participants on myPower connection received communicating smart thermostats.

Notification Given the night before a CPP event.

Elasticity of Substitution myPower Sense: -0.085;

myPower Connection: -0.137.

Reduction Table 2.15 shows the percent reduction of energy relative to the control group.

Table 2.15: Percent reduction of energy relative to control group.

		Percent energy reduction		
Group		TOU-peak days	CPP	Entire summer
myPower Sense	no AC	3%	20%	4.3%
	AC	6%	20%	3.7%
myPower Connection		21%	47%	3.3%

Other Most customers were satisfied with the pilot and would recommend it to friends. Participants felt they were benefiting the environment and were becoming more knowledgeable about energy consumption. Savings were less than expected. The largest area of dissatisfaction is that customers had difficulty programming the thermostats.

References Violette et al. (2007) Erickson et al. (2007).

Xcel Energy TOU Pilot

Utility Xcel Energy.

Program Name TOU Pilot.

Location Colorado.

Dates July 2006 - July 2007.

Tariff description Three tariffs tested:

1. **Time-of-use (TOU):** Two prices - peak (high-price) and off-peak (low-price).
2. **Critical-peak (CPP):** Two price - critical peak (high-price) and off-peak (low price). Maximum of 10 critical peak days in the summer and off peak prices at all other times.
3. **Time-of-use & critical-peak (CTOU):** Same as TOU, with up to 10 critical peak events per summer.

Participants 2,900.

Enabling Technology AC cycling switches and Programmable communicating thermostats for some customers.

Notification Day before for critical peak events.

Reduction Energy reductions are shown in table 2.16.

References Faruqui and Sergici (2009).

Ameren - Power Smart Pricing

Utility Ameren.

Program Name Power Smart Pricing (permanent).

Location Illinois.

Table 2.16: Change in energy use for Xcel Energy TOU pilot during different time periods.

Rate	Enabling Technology	Central AC	Critical-peak	On-peak	Off-peak
TOU	No	No	n/a	-10.63%	-2.95%
	No	Yes	n/a	-5.19%	-0.27%
CPP	No	No	-31.91%	n/a	-0.08%
	No	Yes	-38.42%	n/a	0.59%
	AC Cycling	Yes	-44.81%	n/a	1.34%
CTOU	No	No	-15.12%	-2.51%	8.69%
	No	Yes	-28.75%	-8.21%	3.56%
	AC Cycling	Yes	-46.86%	-10.63%	4.00%
	Thermostat	Yes	-54.22%	-10.29%	2.96%

Dates 2007 - present.

Tariff description Jan 2007 - May 2008: real time MISO hourly prices were charged.

June 2008 - Present: day ahead MISO hourly prices charged.

Participants 2007: 120;

As of January 1, 2009: 3147.

Enabling Technology 105 participants received an energy light in 2008.

Notification When price exceeds 13¢/kWh, notification is given the night before via email or phone. Otherwise customers can check prices on a website.

Average Bill Savings 9% in 2008. Overall, customers had higher bills in the summer and lower bills in the winter, which resulted in the net annual savings.

Elasticity of Demand -0.043.

Average Reduction 0.15kW/customer from 12pm-5pm in the summer;

0.23kW/customer on high price days from 12pm-5pm;

1.5% reduction over entire year: 6% reduction in summer, 0.9% reduction in spring and fall, 3% increase in winter.

Other

- The ultimate objective is to have 2% of the residential market on Power Smart pricing.
- The cost of the hourly meter is $5/month. Participants pay $2.25/month to offset this, the rest is recovered from flat rate customers at an additional 5¢/month.
- This tariff was meant to demonstrate that customers can respond to hourly prices without the aid of expensive technology. Notifications the night before an hour with high prices were meant as a replacement for expensive in home displays.
- There are no economic benefits for customers with extremely low usage, health problems or electric heating (since they already have a subsidized winter rate).
- The program switched from charging real-time prices to charging day-ahead prices because some customers were unhappy with the occasional increase of real-time prices compared to day-ahead prices. Most customers were not even aware of the real-time prices, only the day-ahead prices.
- 62% of customers report checking prices online, 24% of customers do not check prices at all. 30% of customer check prices every day and 30% only check prices after a high price alert.
- 88% of customers reported behavior change.

References Violette and Klos (2009).

PEPCO - PowerCentsDC

Utility Potomac Electric and Power Company (PEPCO).

Program Name PowerCentsDC (pilot).

Location Washington DC.

Dates July 2008 - March 2009.

Tariff description Three different tariffs are being tested:

1. Day ahead hourly pricing (HP). Prices ranged from 1¢/kWh to 37¢/kWh.
2. Critical peak pricing: At most 12 critical peak days in the summer, three in the winter. Events are four hours long. Critical prices were about 75¢/kWh. Non-critical prices were about 10.9¢/kWh. Critical event were called in the summer when temperatures exceeded 90°F and in the winter when temperatures fell below 18°F.
3. Critical peak rebate. Rebates were given for reduction below a customer baseline during critical events. Critical rebates were about 75¢/kWh. Non-critical prices were about 11¢/kWh.

Participants Program participants are shown in table 2.17.

Enabling Technology About half of customers received a smart thermostat which can respond to high prices and is capable of remote meter readings. It is automatically programmed to turn off the AC during a peak event, however customers can override it.

Table 2.17: Participants in PowerCentsDC pilot. All electric customers have electric space heating.

Customer type	CPP	CPR	HP	Control	Total
Regular	175	202	175	128	680
All electric	58	62	56	97	273
Regular limited -income	0	36	0	94	130
All electric limited-income	0	18	0	59	77
total	233	318	231	378	1160

Notification Day ahead prices can be checked by website or phone call. The smart thermostat also shows prices in real time. HP customers were notified when prices exceeded a high threshold of 23¢/kWh in the summer and 15¢/kWh in the winter. Critical peak notifications are given by 5 pm the day before via: SMS, email, phone or smart thermostat.

Bill savings Bill savings are in table 2.18.

Table 2.18: PowerCentsDC annual bill savings.

Price plan	Annual bill savings	
	$	%
CPP	1.56	2
CPR	4.59	5
HP	43.02	39

Reductions Peak reductions are in table 2.19.

Table 2.19: PowerCentsDC peak reductions.

Price plan	Peak reduction (%)			
	Summer	Winter	at 85°F	at 97°F
CPP	34	13	26	43
CPR	13	5	8	20
HP	4	2	3	3

References eMeter (2010), Wolak (2010).

2.2.2 Comparison of dynamic pricing tariffs

The average demand reductions for the CPP pilots are shown in figures 2.2. Figure 2.2 shows the average demand reductions for the TOU and RTP programs. Note that it is the reduction during the highest price period; for CPP pilots, this means critical hours. The values for the TOU pilots are sometimes calculated on critical peak days, even though the critical peak tariff was not applied to the TOU participants. In figures 2.2 and 2.3 it appears that CPP more effectively induces behavior change than RTP and TOU, since the figure shows customers reduce demand by more significant quantities. It is important to note that this does not necessarily mean that CPP is the most effective tariff design for several reasons:

1. The different tariffs are not comparable due to differences in population, price, weather and other factors. It is therefore difficult to draw conclusions by comparing the tariffs.

2. If the goal is peak demand and capacity reduction, the important number is the aggregated (i.e. the collective response of all customers) *worst* (smallest) response during a high price period. The values reported in figures 2.2 and 2.3 are average values. The numbers reported by utilities are typically average or highest response.

In the five cases where customers were given enabling technology to automatically control load with respect to price, customers were able to reduce demand significantly more than those who did not have enabling technology. This will likely hold in any tariff design, since the technology, if properly programmed, can automatically respond, while people must put thought and effort into a response. The question remains, however: is this additional response worth the cost of the technology?

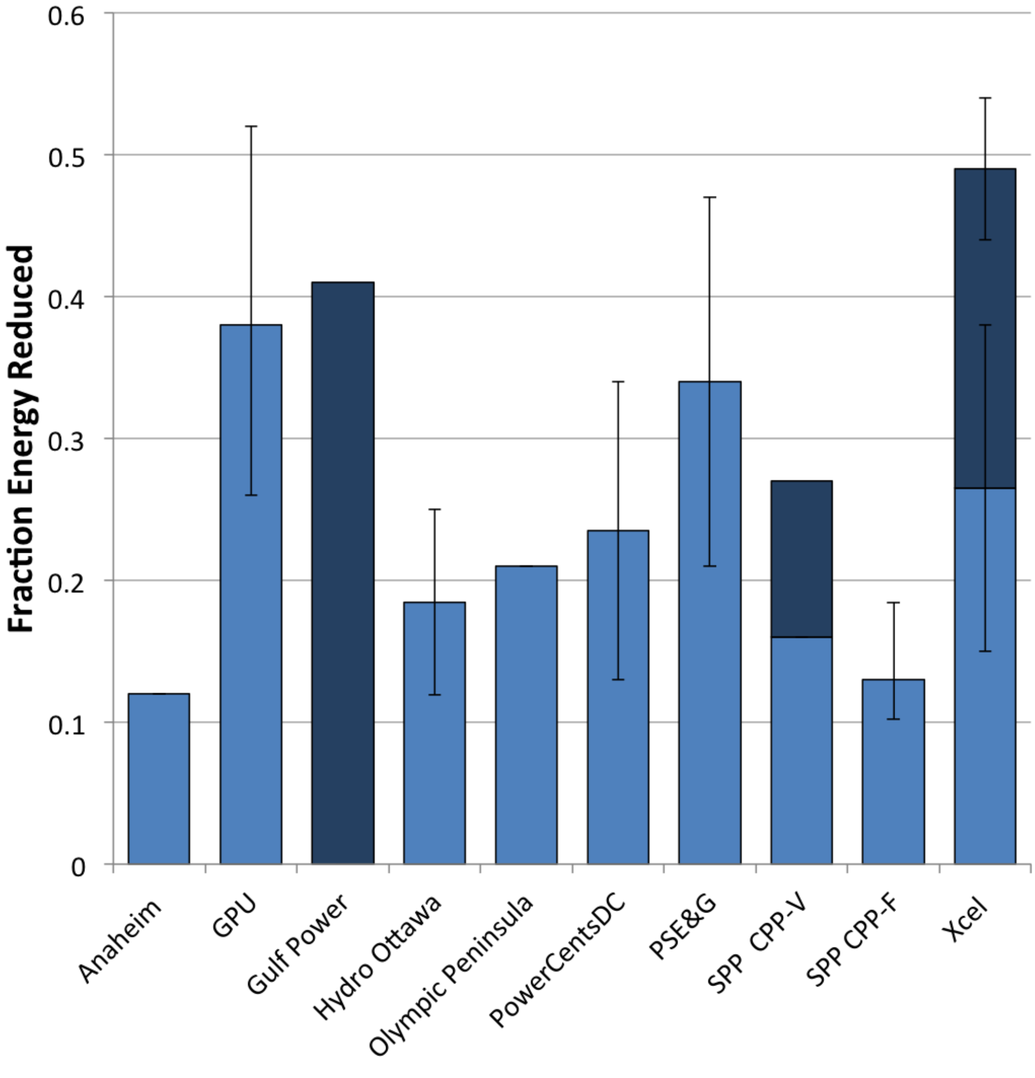

Figure 2.2: Average reduction for CPP calculated during critical peak hours. Reduction with enabling technology (technology that automatically turns off load) in darker color. Error bars indicate range of values reported for that program.

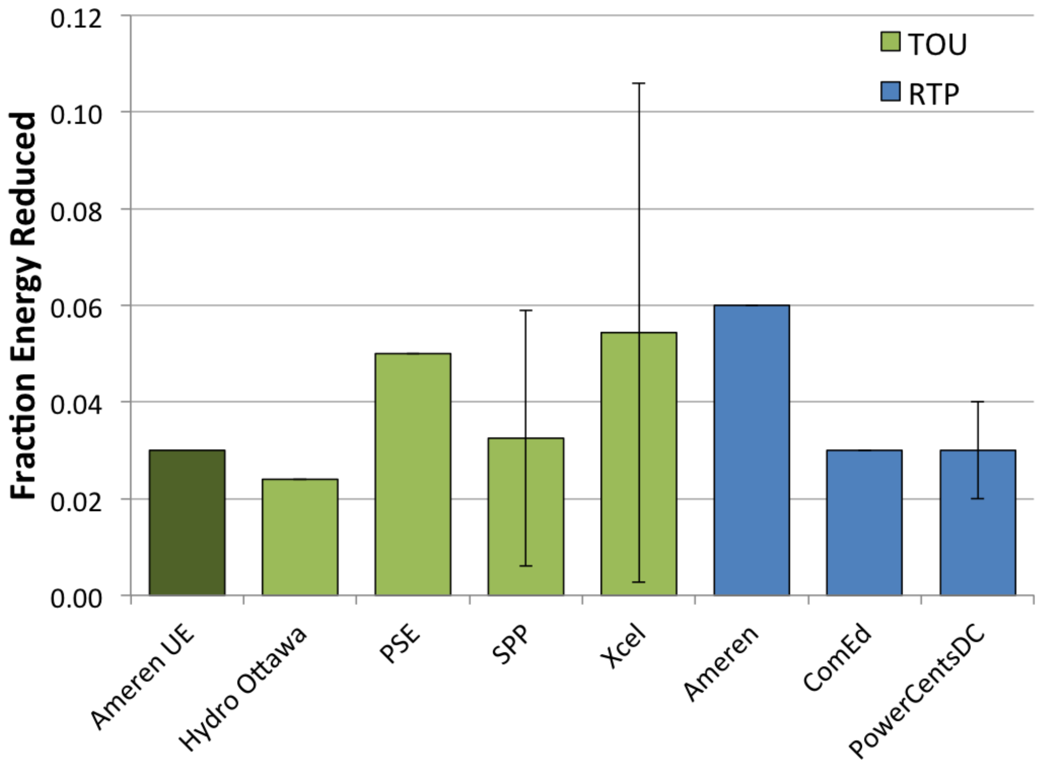

Figure 2.3: Average reduction for TOU (calculated during peak hours, on critical peak days where applicable) and RTP programs. Reduction with enabling technology (technology that automatically turns off load) in darker color. Error bars indicate range of values reported for that program.

Table 2.20 shows the range of elasticity of demand, elasticity of substitution and percent energy reduction during high price hours from the tariffs listed in section 2.2.1.

Although all the pilots cited here show that customers are responsive to price on average, they do not characterize the probability of response, or how reliable customers are in aggregate. There is reason to believe that customers are not consistent in their response, and that this inconsistency is correlated across customers. This presents a problem, since if all customers stop responding at the same time, capacity and spinning reserves cannot be reduced, which significantly reduces the benefits of dynamic pricing. In ComEd's RTP pilot for example, it

Table 2.20: Highest and lowest non-zero values from the tariffs in section 2.2.1 for percent energy reduction during high priced hours, elasticity of demand and elasticity of substitution.

	Percent energy reduction		Elasticity of demand		Elasticity of substitution	
Group	Low	High	Low	High	Low	High
TOU	2.4%	7%	n/a	n/a	n/a	n/a
CPP	12%	47%	-0.02	-0.044	$-.077$	-0.111
RTP	n/a	n/a	-0.04	$-.09$	n/a	n/a

was found that customers respond extremely well for the first 2 hours of high prices, but if prices are high for 3 hours or more, response falls off sharply (Summit Blue, 2004). In both the ComEd Pilots and the California CPP Statewide Pricing Pilot if prices are high for only 2 hours at a time, but for 3 or more days in a row, response falls sharply on the third day (Charles River Associates, 2005; Summit Blue, 2004). It is important to understand the reasons why response falls off and how to induce customers to keep their response up. Before dynamic residential tariffs can be implemented widely, it is important to characterize the probability of customer response.

Another issue that is unclear from the previous pilots is how customers shift usage from peak to off peak periods. All the pilots that have calculated if a shift exist, have determined that customers do in fact shift some usage from peak to off peak periods. However some indicate that customers still conserve overall, while others indicate that net energy usage actually increases.

The most important thing to take away from this literature review is the importance of testing a tariff in a pilot before making it permanent. Puget Sound Energy's (PSE) TOU program (see section 2.2.1) was cancelled less than two years after it was introduced because of customer dissatisfaction and negative media coverage. Most customers actually saw a net increase in their bills. Had PSE piloted the tariff first, it may have been able to design a better tariff before placing

300,000 customers on it. Ameren had to change its tariff based on hourly real-time prices to a day-ahead hourly tariff because customers found it too complicated.

Another argument for piloting new tariffs before full implementation is the difference in circumstances between the service areas of different utilities. This makes it difficult to design a tariff in one area based on a pilot in a different area. Some utilities have drawn opposite conclusions from dynamic pricing tariffs. For example:

- ComEd and Ameren both have hourly tariffs in Illinois. After four years of offering a day-ahead tariff, ComEd successfully switched to a real-time tariff. Ameren started with a real-time tariff, but switched to a day-ahead tariff after receiving negative feedback about the real-time tariff.

- The California Statewide Pricing Pilot found large single-family homes to be the most responsive to price while ComEd found multi-family homes to be most responsive[1].

- The AmerenUE study found that consumers are not responsive to TOU tariffs, but Hydro Ottawa and Puget Sound Energy found that consumers reduced usage in response to TOU.

- The Olympic Peninsula Project found that customers on hourly tariffs did not change their net energy usage over an entire year, while Ameren found that customers on its hourly tariff reduced their total energy usage over an entire year.

An important piece of information that is absent from the literature on the pilots is the value of shaving a kW of demand. Implementing a dynamic tariff is not cheap – smart meters need to be installed, customers need to be educated, and

[1] This may be due to differences in how ‘responsive’ is defined

a communication infrastructure is necessary. Enabling technology for customers is an expensive option. The question is how much should utilities and taxpayers spend on reducing demand? How does the value of reducing a kW of demand increase as the probability of reducing that kW increases? The value of reducing a kW must be quantified before more money is spent on demand response.

Chapter 3

Equity in Residential Electricity Pricing

3.1 Introduction

Wholesale and retail electricity prices are decoupled for most residential electricity customers. Wholesale prices change in real time to reflect marginal cost and can range from negative values to $1000/MWh[1] (PJM, 2009). Residential retail rates are typically flat rates, which are load weighted averages of expected price over a certain period of time[2] (typically a year or more). Flat rate (FR) pricing is inefficient because price does not reflect marginal cost, so customers may be under- or over-consuming at any point in time (Borenstein and Holland, 2005; Spees and Lave, 2008). Customers with a high coincident peak relative to their

*A version of this chapter was submitted to the Energy Journal as "Equity in Residential Electricity Pricing" (submitted: February 2012, revised October 2012) by Shira Horowitz and Lester Lave.

[1]In the PJM Interconnection, a regional transmission organization serving 13 US states.

[2]Some utilities offer residential customers alternative tariffs including: time-of-use pricing, critical-peak pricing, real-time pricing, inclined block pricing.

average demand are, on average, paying below marginal cost[3] while customers with flatter usage or those whose peak demand occurs at off-peak prices are paying above the marginal cost they impose, on average (Spees and Lave, 2008). Customers that add to peak load impose high costs on the system, but under FR pricing, all customers pay the same amount. This is a policy where customers with high coincident peaks are receiving a cross-subsidy from the remaining customers.

Real-time pricing (RTP) has the potential to address these problems by directly coupling retail and wholesale prices. The energy charge in a residential RTP tariff changes hourly to reflect either the day-ahead or real-time locational marginal energy price (LMP). This provides a signal for customers to use only the amount of power that they value at or above the current marginal price of power. If customers respond to high prices by lowering usage, RTP can potentially lead to lower peak demand and price. Even if only some customers respond, all customers can potentially benefit from lower marginal price and lower capacity costs due to lower peak demand. Charging customers the RTP is no guarantee that customers will reduce or shift load when price is high. The potential savings must be large enough for customers to invest in the time, education and technology necessary to effectively reduce peak demand. Several utilities including Commonwealth Edison (ComEd) and Ameren currently offer optional RTP tariffs to residential customers. Other utilities offer approximations of RTP such as time-of-use (TOU), where days are divided into peak and off-peak prices for electricity or critical-peak pricing (CPP) where higher prices are triggered by high wholesale prices or a correlated metric such as temperature.

Borenstein and Holland (2005) show that increasing the share of customers on real-time pricing is likely to improve efficiency. Borenstein (2005) shows that even

[3] The total price of electricity is set to average cost, not marginal cost. Average cost can be greater than marginal cost (high fixed costs) or lower (in systems where there is a limited quantity of cheap power). We refer here only to the portion of the price that is for energy.

with small elasticities, gains in economic efficiency from RTP can be substantial. We will not elaborate any further on the inefficiencies of flat rate pricing and the potential efficiency gains from dynamic pricing, since there is already substantial literature on this subject (Borenstein et al., 2002; Borenstein and Holland, 2005; Holland and Mansur, 2006; Spees and Lave, 2007; Borenstein, 2005). Instead we will focus on the distributional impacts of dynamic pricing.

Here, we address a question of practical importance to electric utilities and public utility commissions who are considering a move to dynamic pricing: which consumers "win" (will save money under RTP compared to FR) and which consumers "lose" (lose money under RTP compared to FR) when switching from FR to RTP? Because of the inherent cross-subsidies between customers under FR pricing, when a utility switches to dynamic pricing, the cross subsidy will be reduced (CPP) or disappear entirely (RTP), and the cost burden will shift from customers with flatter loads or non-coincident peaks to those with high coincident peaks. Some customers may experience significant changes in their bills – both increases and decreases if they don't shift their usage. It will be important for utilities and PUCs to know in advance which customers will have large bill increases, so they can supply those customers with information and tools to help mitigate the increased bill by increasing energy efficiency or shifting or curtailing load, or create policies to tax the "winners" and subsidize the "losers".

The question can be reframed for those utilities that are not considering a switch to RTP: which customers are currently providing cross-subsidies to other customers under FR pricing? Is the wealth transfer caused by the cross-subsidies an acceptable policy from an equity perspective?

We address these questions by taking a sample of customers and calculating their bill difference under RTP and FR under both inelastic and elastic demand. We treat the scenario with inelastic demand as a zero-sum game used to explore cross-subsidies: one customer's loss is another's gain. This is also a "worst case scenario" for RTP programs, where consumers don't respond, so there are no net savings to consumers. Under elastic demand, there are net savings to consumers due to avoided energy usage, lower marginal prices and lower capacity costs. We then analyze customer characteristics including income and demand. We obtained data from a sample of ComEd customers.

Borenstein (2012) and Faruqui et. al. (2010) also perform empirical analyses of the distributional effects of dynamic pricing. Our analysis differs in several ways: we use an RTP tariff while the other analyses focus on variations of TOU and CPP; we focus on different geographic regions which have different load and price characteristics; our analysis assumes a mandatory tariff, while the other analyses assume opt-in tariffs for their distributional calculations.

We find that under inelastic demand, only 36% of consumers would save money under RTP. With elastic demand of -0.2 (an upper bound), roughly 50% of customers would save money from reductions in energy usage and energy price. Many more customers save if we assume reductions in capacity costs due to demand response. The customers who save tend to be the largest consumers, while those who would lose money under RTP tend to be smaller consumers and represent a disproportionate amount of low-income customers.

The remainder of this chapter is organized as follows. Section 3.2 describes the data set. Section 3.3 explains the analysis for inelastic demand and 3.4 models elastic demand. Section 3.5 gives the policy implications of the analysis.

3.2 Data set

Usage

ComEd serves Northern Illinois and the greater Chicago area and is part of the Regional Transmission Organization PJM Interconnection. ComEd has an optional residential RTP tariff currently in use, so we were able to use actual tariffs (adjusted to be revenue neutral, see appendix B) in our calculations. We have hourly electricity data from a stratified sample of 1260 residential customers from 2007 and 2008. Some of the strata were oversampled, however corrections were made for this in all statistics using the bootstrap method (appendix C). While simple weighting is adequate to get point estimates for the mean, etc. bootstrapping is necessary to obtain a distribution with confidence intervals.

These customers were all on a residential FR tariff, so there are no confounding behavioral factors due to exposure to RTP. We know which of four customer classes each customer belonged to: (1) single family (SF); (2) multi-family (MF); (3) single family with electric space-heat (SFH); and (4) multi-family with electric space heat (MFH) (see table 3.1 for summary statistics). We also have data on whether customers received any need-based subsidies (table 3.1). There are several income-based subsidies customers can qualify for[4]. We classified any customer that received any need-based subsidy at any point over 2007 or 2008 as "low income". Approximately 6% of customers in the population are low income by this definition.

The raw data, consisting of hourly household electricity usage were cleaned and verified so that all remaining data were valid. The protocol used for cleaning the data is in appendix D.

[4]The subsidies are: Low Income Home Energy Assistance Program (LIHEAP) Payment, ComEd Space Heat Credit, Summer Bill Credit, Rate Relief Credit, Residential Special Hardship and Chicago Housing Authority (CHA-CARE) All Clear Credit.

Table 3.1: Summary statistics by customer class in ComEd population and sample for 2007-2008.

Customer Class	Total accounts	Percent (pop.)	Accounts (samp.)	Subsidized (samp.)	Avg. usage (kWh/h)
Single family (SF)	2,200,000	64.8	344	13	1.3
Multi-family (MF)	1,000,000	29.7	264	17	0.5
Single fam. sp.-heat (SFH)	35,000	1.0	169	6	3.9
Multi-fam. sp.-heat (MFH)	155,000	4.5	482	89	1.4
Total	3,400,000	100	1259	125	1.1

3.2.1 Tariffs

ComEd residential electricity bills are monthly bills and consist of three sections: (1) electricity supply services, (2) delivery services, and (3) taxes and other. There are several different charges in each section. Some charges are the same for both RTP and FR customers; some charges are different and in some cases a charge is exclusive to either RTP or FR. Charges can be either fixed monthly costs or based on the amount of electricity consumed that month (i.e. a cost per kWh). The one exception is the capacity charge, which is applied only to RTP bills. Customers are billed per kW-month of demand, where demand is the customer's average usage during the 10 hours of highest system usage. Appendix A gives details on the rates and how bills are calculated. Table3.2 shows the average annual bill for each customer class.

Table 3.2: Average annual bill over 2007-2008 in a revenue neutral scenario.

Customer Class	Percent (population)	Avg. annual bill ($/yr)
Single family	64.8	1290
Multi-family	29.7	560
Single family space heat	1.0	2530
Multi-family space heat	4.5	970
Total	100	1070

For customers that are on RTP, the only portion of the bill that changes hourly is the energy supply charge, which corresponds to the wholesale LMP. Over 2007 and 2008 the RTP energy supply charge ranged from -25¢/kWh to 50¢/kWh with a mean value of 5¢/kWh, a median of 4¢/kWh and a standard deviation of 3¢/kWh. 90% of prices were between 1¢/kWh and 10¢/kWh, while 50% of prices were between 3¢/kWh and 7¢/kWh. Prices exceeded 15¢/kWh 1% of the time. The RTP energy supply charge represents 45% of the total average annual electricity bill[5].

The flat rate energy supply charge ranged from 4.4¢/kWh to 7.6¢/kWh depending on the month and customer class[6]. All other rates (both marginal and fixed), for both FR and RTP are constant throughout each billing cycle, but may be adjusted, no more frequently than monthly, to reflect changes in cost.

3.3 Analysis: no behavior change

In this section we calculate the difference in annual electricity bill for the sample, had the customers been on RTP, compared to what they actually paid under FR. It should be noted that all of the customers in the sample were on the FR, and were at no point on RTP during this time period. We apply the RTP tariff that was optional for ComEd customers at that time to the electricity usage of the customers in the sample.

We calculate the difference in annual electricity bills for the sample of customers, had they been on RTP without any behavior change. The goal of RTP is to give consumers a price signal so that they can modify their behavior, however

[5]This calculation, as well as all other calculations in this chapter does not include taxes, so in reality the supply charge represents a smaller portion of the total bill.

[6]It should be noted that the energy supply charge for FR customer includes the capacity payment, but is a separate charge for RTP customers, so the energy supply charge under FR and RTP are not comparable.

there is no guarantee of behavior change. Price differentials must be large enough for customers to save money, the prices must be communicated effectively, and consumers must have the resources to react. We first compare bills with the assumption of no behavior change for several reasons: (1) it provides a worst case scenario for bill changes, (2) it gives us information on residential cross subsidies under flat-rates, and (3) it informs us which customers need the most help from utilities in controlling bills and technology for behavior change under switches to dynamic pricing.

3.3.1 Assumptions

In order for the results to be applicable to other utilities, we proceeded as follows. All subsidies are removed from the analysis so it can be generalized to areas that do not have these subsidies. ComEd space heating customers receive a significant subsidy on their energy supply charge (ranging from 2.4 - 2.8¢/kWh depending on season and customer class, or roughly 1/3 of the energy supply charge). This subsidy was removed from the analysis. The first 100,000 RTP customers in ComEd receive a $5 subsidy on their smart meter lease. This subsidy is not included in the analysis, so the analysis can be applicable to rollouts where there will be no meter subsidy. Low income subsidies were not included when calculating bill differences, since it is presumed that the same subsidy would be applied under FR or RTP, and the FR and RTP bills are differenced.

The charges in the electricity supply services portion of the bill are pass-throughs, and go directly to PJM or the generators to cover the associated costs. In theory, if customers consume the same amount of energy at the same times, the total energy supply costs should be the same under RTP or FR. However, this does not occur because at present ComEd procures power for FR customers via a combination of long term contracts and spot market purchases, while all of the RTP energy is purchased directly on the spot market. Due to hedging premiums and the lack of perfect foresight for future spot market prices, the cost of power under long term contracts is not the same as the equivalent power bought on the spot market. If there were to be a larger shift towards RTP however, buying all RTP power on the spot market as is currently done would not be feasible. In order to provide generators and the market with the certainty they need (to acquire capital at reasonable rates) long term contracts are necessary (Hirsch, 1999). To account for this, we have adjusted the FR bills to be revenue neutral with RTP, so that the total revenue under either rate is the same, it is just distributed differently amongst customers. See appendix B for details on revenue neutral calculations.

Even with these assumptions, these results may not be generalizable to other utilities and regions. Generation profiles (i.e. availability of coal, oil, etc.), demand profiles, customer makeup (i.e. industrial, commercial, residential), transmission constraints and weather are just some of the factors specific to each utility and region that can change these results. The data we have comes from a summer-peaking utility. Result would be significantly different in a winter peaking area. Nevertheless, the lessons learned here can inform policy makers in other areas and justify the need for further study.

3.3.2 Results

Figure 3.1 shows the distribution of percent bill changes for ComEd customers had they been on RTP compared to FR with inelastic demand and a 95% confidence interval (CI). Negative percent changes indicate a savings on RTP relative to FR. Roughly 36% (95% CI: [34% - 39%]) of customers would have done better under RTP compared to FR, while the remaining 64% of residential customers would have lost money had they been on the RTP tariff without shifting or curtailing any of their usage in response to fluctuating prices. Under RTP, the bills of approximately 70% of customers fall within 10% of their FR bills. 10% of customers will see a significant increase: 20% or more in their annual electric bills. About 1% will see an increase greater than 30%. The median customer would lose $25 [$23-$27] per year if she switched to RTP. As a check that we properly performed the revenue neutral adjustment, the mean change in bill is statistically indistinguishable from zero (mean change of -$0.37/yr [-$5.10yr, $3.80/yr]).

Another way of framing this is that under the current FR pricing, 36% of residential customers are providing a cross-subsidy to the remaining residential customers. This is because 36% of customers use more power when power is below average price, while the remaining customers use more power when power is above average price. We will explore the reasons behind this result in the remainder of this section.

The distribution in figure 3.1 is asymmetric. Despite the fact that the analysis was done so that the switch to RTP would be revenue neutral (i.e. gross revenue from residential customers is the same under RTP and FR), all of the savings go to just 35% of the customers. Another asymmetry is that the maximum savings is 20% while the maximum loss is more than double, exceeding 40%. When the distribution is plotted against the absolute bill change instead of the percentage of bill change, as in figure 3.2, the distribution, of course, still crosses zero at the same place, but the asymmetry with respect to the vertical axis is now switched and more exaggerated – in absolute terms the maximum savings ($1000) is an order of magnitude larger than the maximum loss ($150). Only 36% of customers would save in a zero-sum tariff switch, but these customers save more money, even though they save a smaller fraction of their bills. The 64% of customers who lose

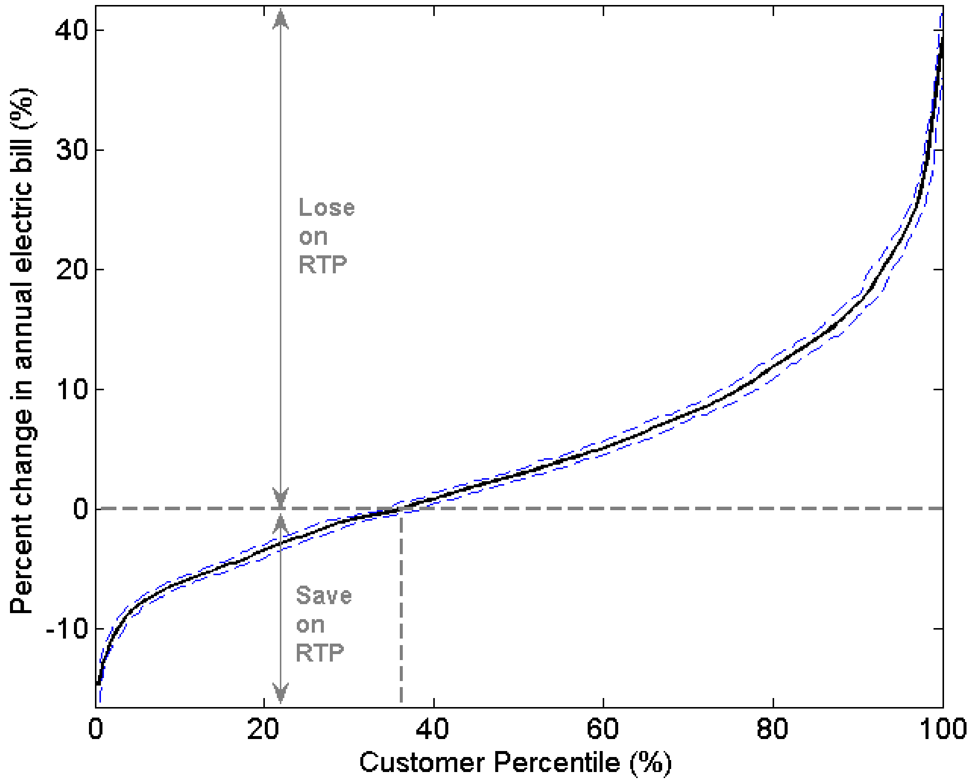

Figure 3.1: Distribution of annual bill changes, as a percent change from flat rate bills for all customers with 95% confidence interval.

money under RTP lose a smaller magnitude of money, but that represents a higher fraction of their annual bills.

Figure 3.3 shows change in bill as a function of average hourly household energy consumption and shows that the relationship is roughly inversely proportional. There is a positive correlation between customers with high consumption and those who would have saved more under RTP, while those who consume less electricity tend to lose under RTP. Under the current FR, the largest users are providing a cross-subsidy to smaller customers.

In order to understand why large customers consistently save under RTP and small customers consistently lose, we analyze how each segment's usage coincides with price. Price has both a daily and seasonal cycle. The daily price profiles for

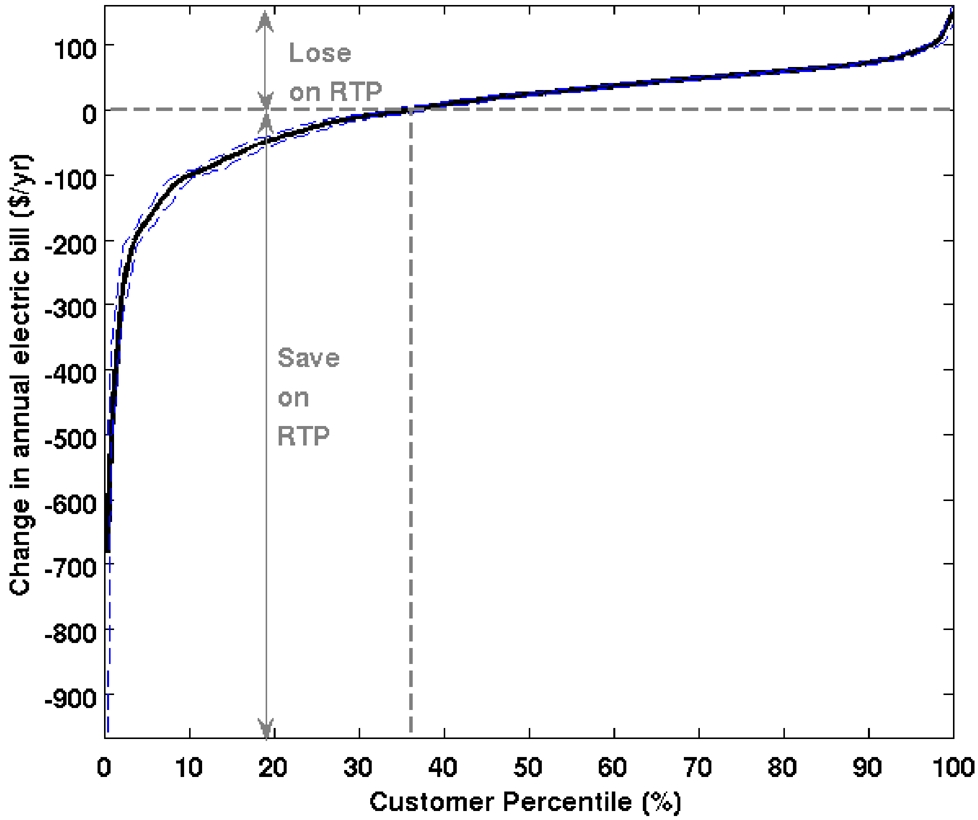

Figure 3.2: Distribution of annual bill changes for all ComEd customers in $/yr with 95% confidence interval.

summer, winter and overall 2007-2008 are in figure 3.4. In ComEd's region, the seasonal cycle is that price peaks in the summer and is lowest in fall and spring. In the summertime, daily price follows temperature, peaking at around 4 p.m. and reaching a low near 3 a.m. In the winter, price dips during the hottest part of the day.

We now look at the usage patterns of the 5% of customer who save the most under RTP and the 5% of customers who lose the most under RTP, and examine how the interactions between price and usage determine the winners and loser. Figure 3.4 shows the load profiles for the top and bottom 5% of customers for the summer, winter and the entire year. The customers who win under RTP use

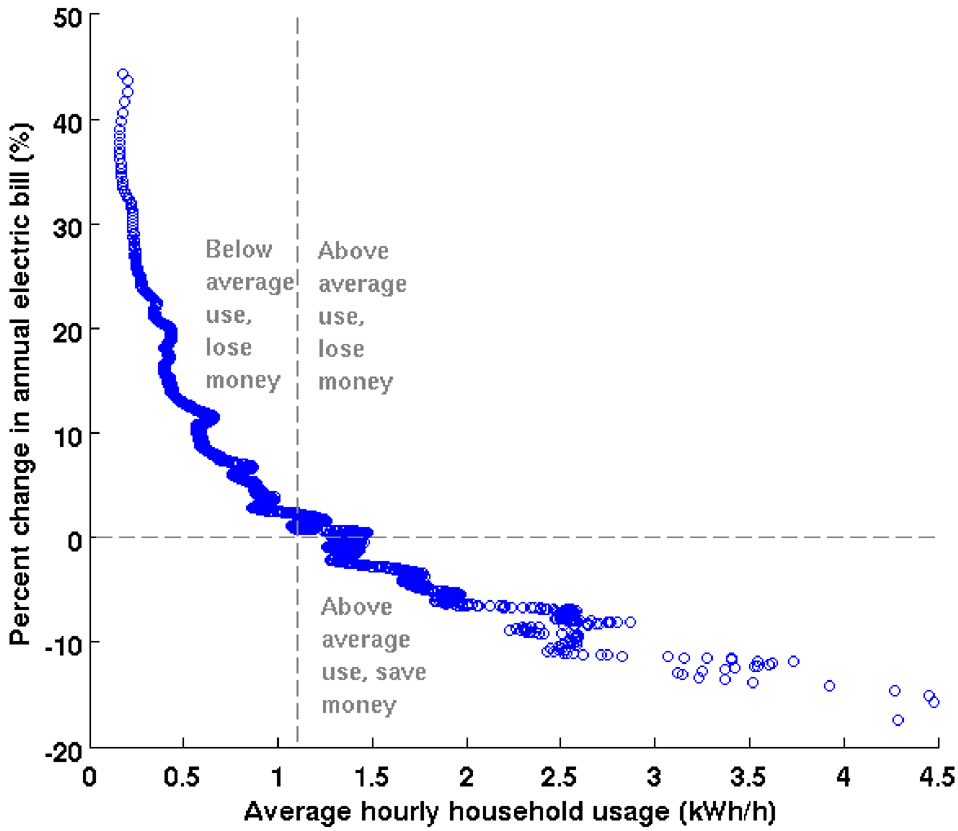

Figure 3.3: Average hourly household electricity consumption vs. absolute annual difference in bills. Points shown are averages from a bootstrap, in order to be representative of the population.

a lot of power, however they using a lot of power all the time – summer, winter, day, night. They have a higher base-load (the minimum amount of power they use). Those who lose under RTP are using very little power, however when they do use power, it is during times of high price – during the summer, during the afternoon. They have low base-loads and high peaks. The ratios for average peak to base usage for the top 5% winners and losers is in table 3.3. The reason larger customers save under RTP is because they are using a lot of power when power is cheap – not because they use little when it is expensive.

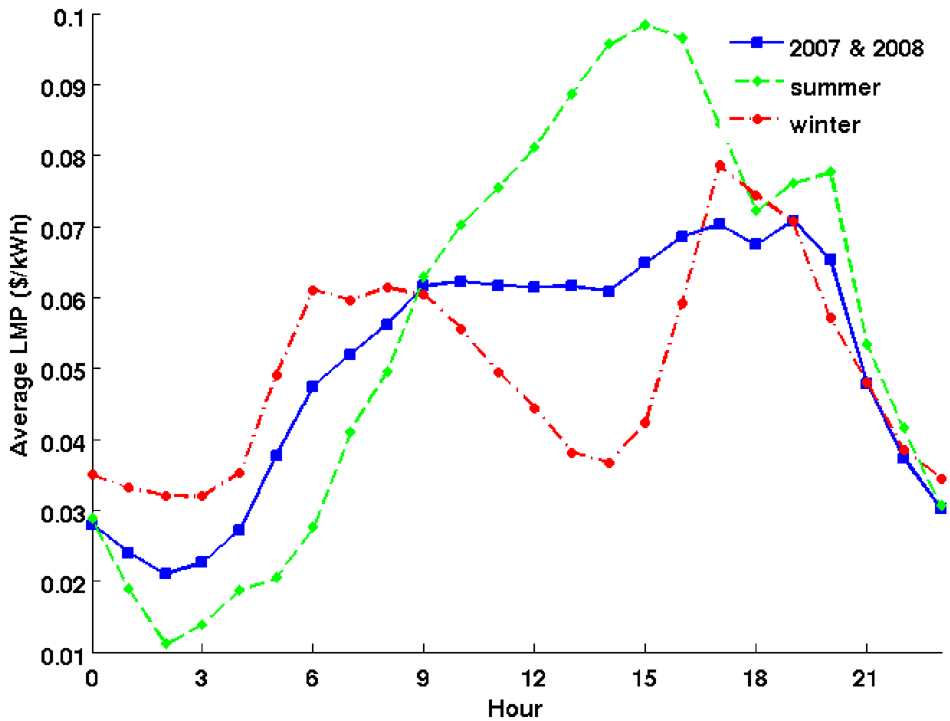

Figure 3.4: Daily locational marginal price (LMP) profile for ComEd for 2007-2008.

Table 3.3: Ratio of average daily peak to base usage for the top 5% biggest winners and losers under RTP.

	Winners	Losers
Entire year	1.4	1.8
Winter	1.2	1.8
Summer	1.5	2.2

It should be noted that the load profile for the winners is dominated by electric space heating customers, which is why the load profiles are winter peaking. If these customers are removed, the load profile for the winners switches to summer peaking, however the implications remain the same: the ratios of summer to winter usage and peak summer usage to base summer usage is lower for winners than losers despite the fact that the average usage of winners is much higher than losers.

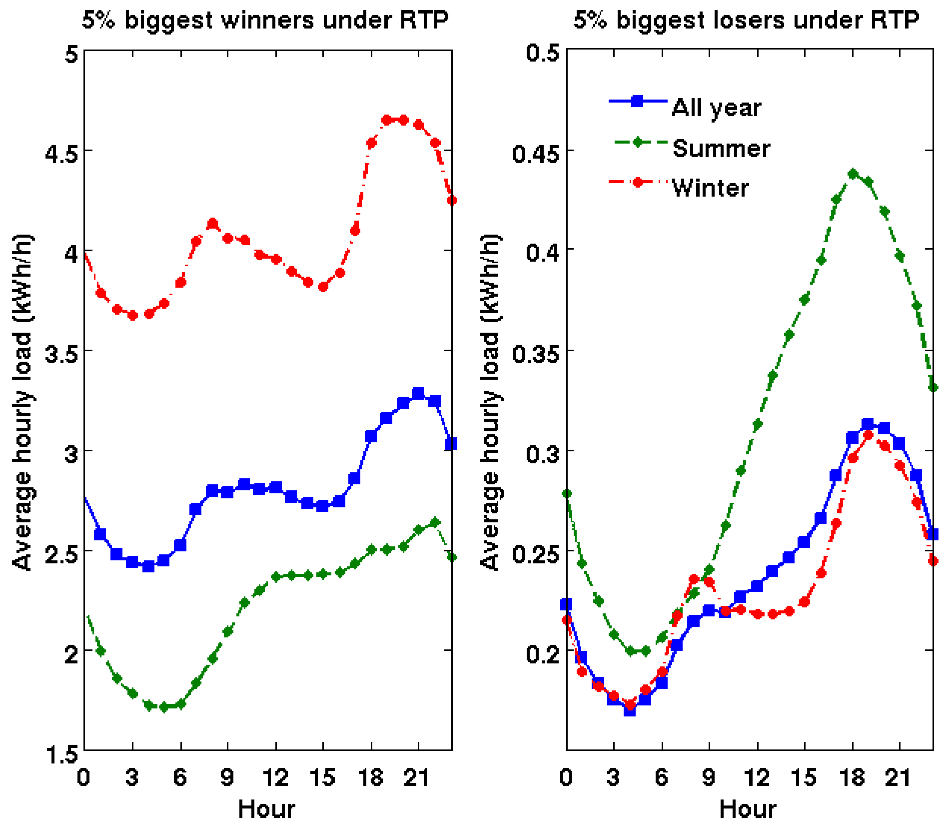

Figure 3.5: Average load for the 5% of customers who save the most under RTP (left) and 5% of customers who lose the most under RTP (right).

3.3.3 Low income customers

Figure 3.6 shows the distribution of bill change for low income customers and the remaining customers. 19% of low income customers would save under RTP, while 37% of non-low income customers would save. This is not because low-income customers use power differently from similarly sized regular customers – in fact, their usages are, on average, statistically indistinguishable at the 95% confidence level. The lower rate of savings under RTP for low-income customers is an artifact of low-income customers having lower than average usage for their customer class, and smaller users tending to lose money on RTP.

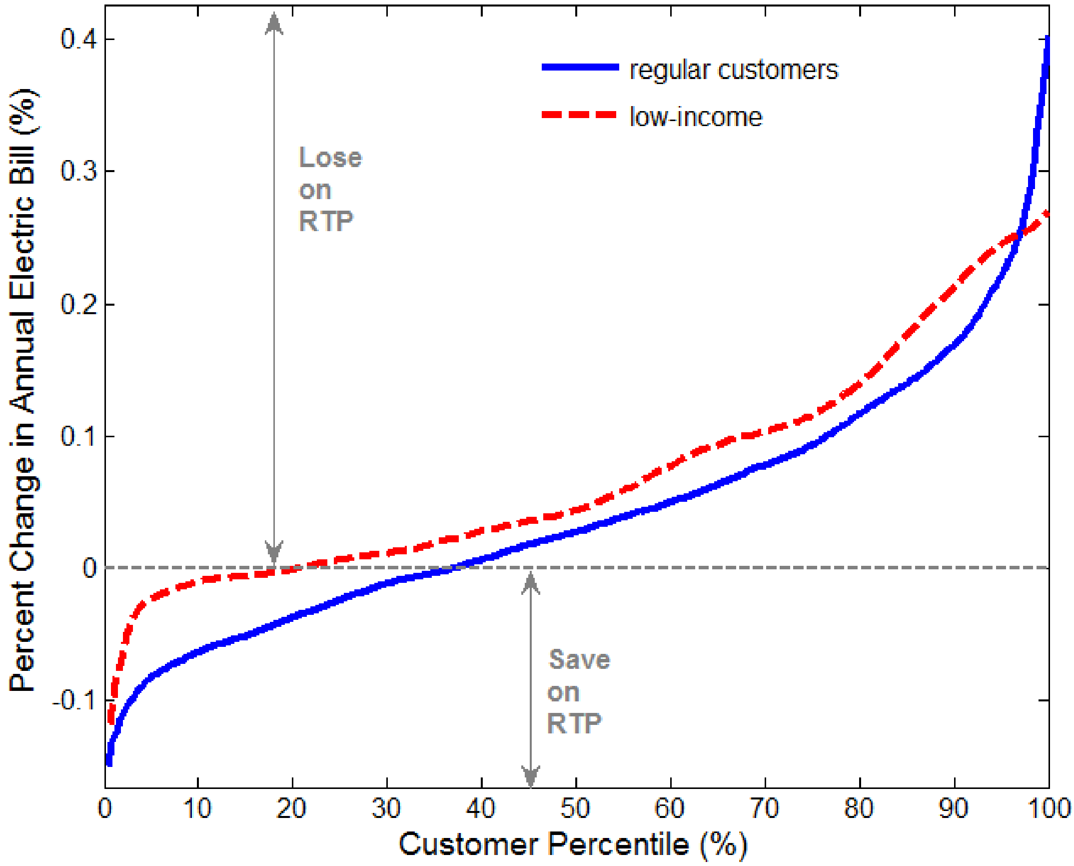

Figure 3.6: Distribution of bill change for low income customers and the remaining customers.

3.3.4 Customer class

Figure 3.7 shows the distributions for bill change by the four customer classes and table 3.4 shows the percent of customers in each customer class who would have saved under RTP. Space heating customers (SFH and MFH are 5.5% of the population) tend to save the most under RTP because they are winter peaking, and price tend to be lower in the winter. SF customers tend to save more than MF customers which is correlated with the fact that they tend to use more power.

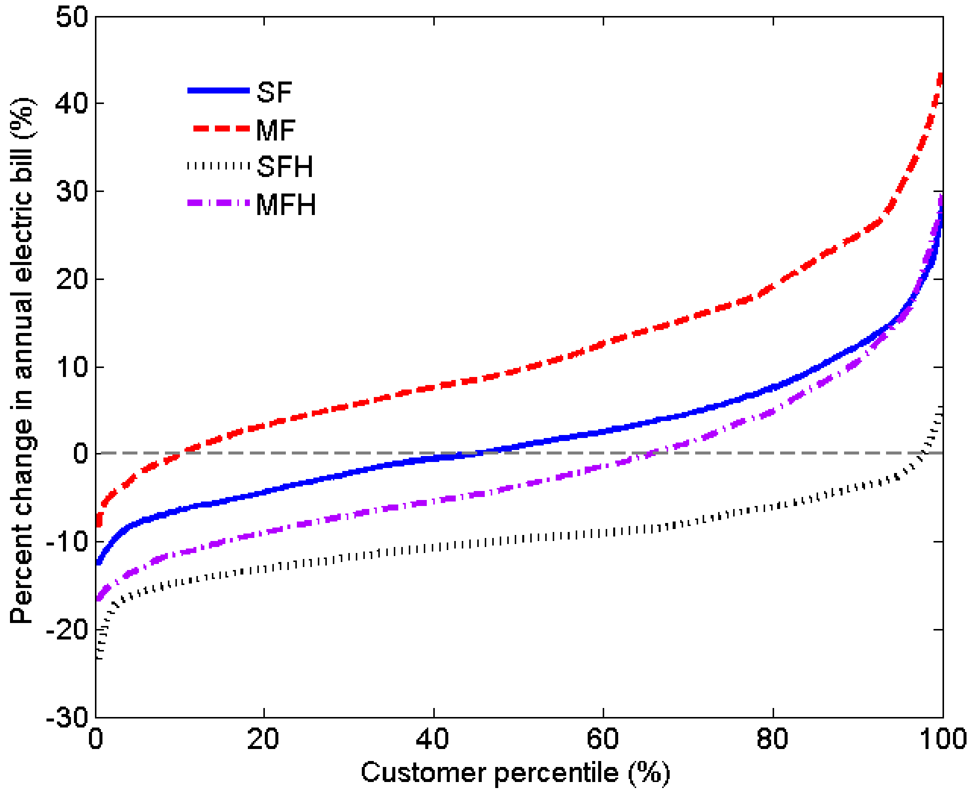

Figure 3.7: Distribution of percent change in annual electric bill under RTP compared to FR by customer class.

Table 3.4: Percent of customers who would have saved under RTP by customer class.

Customer Class	Customers (percent)	[95% CI]
Single family (SF)	45	[40 49]
Multi-family (MF)	11	[8 14]
Single family space-heat (SFH)	98	[96 100]
Multi-family space-heat (MFH)	65	[62 69]

3.3.5 Comparison with other studies

In similar analyses Borenstein (2012) and Faruqui et al. (2010) have different results. Borenstein analyzed distributional effects for opt-in CPP and TOU tariffs for Pacific Gas and Electric (PG&E) and Southern California Edison (SCE) customers and found that low consumption houses see bills decline under dynamic pricing, while high consumption households have higher bills. In an analysis of programs in the District of Columbia, Baltimore, Connecticut and California, Faruqui et. al. found that low income customers can benefit from dynamic pricing without changing behavior. However, the general result amongst all three analyses is the same: most consumers will see little impact to their electricity bills under dynamic pricing.

There are several possibilities for the divergences in our results. We use different regions in our analyses which will result in different usage and price patterns. Different weather in different regions will further change usage patterns. Borenstein's and Faruqui et. al.'s analyses focus on TOU and CPP which do not change prices across seasons, while RTP (in our example) has a significant seasonal cycle. Seasonal usage patterns dominate the overall cost shifting in our example, which is not present in the analyses with CPP and TOU. The finding that low-income consumers tend to save in the other analyses, while they tend to lose in our analysis is an artifact of the fact that low-income households tend to be low-consumption households: since low-consumption households tend to lose, low-income households tend to lose as well.

3.4 Elasticity of demand

The objective of RTP for residential customers is to get an increase in economic efficiency by exposing customers to marginal cost. There is no guarantee of a response – the change in price must be large enough for customers to deem a response worthwhile, prices must be properly communicated and customers must have the means to shed or shift load, including: discretionary load, time, education and automated technology. There is evidence that customers do respond to real time rates. An analysis of the Ameren Power Smart Pricing program (an RTP tariff in Illinois) found an elasticity of demand of -0.043 (Violette and Klos, 2009). The ComEd Energy Smart Pricing Program (RTP pilot) was found to have elasticities[7] ranging from -0.042 to -0.117 for different strata (Summit Blue, 2007). However, these pilots have biases, including volunteer selection bias and intervention bias which may lead to a significant overestimation of the elasticities (Davis et al., 2012).

In this section we assume customers respond to increased marginal prices by lowering their electricity usage. Unlike the previous analysis, this is no longer a zero sum game – if some customers respond then there should be a net savings to society. There are several mechanisms through which customers can save: (1) if they reduce their load, then they are not charged the higher prices at that time for using power, (2) if customers shift load to a time when price is lower, they are charged the lower price, (3) if enough customers reduce load to reduce the marginal price, then all customers pay a lower price and (4) if enough customers reduce load to reduce the capacity needs for the region, then all customers pay lower capacity costs.

3.4.1 Assumptions

We apply the same assumptions used in section 3.3 with some additions. We assume that customers respond with a non-linear price elasticity of demand. We assume that customers respond only when price exceeds a certain threshold: $P > P_T$. Below P_T we assume that consumers have a satisficing "deadband"

[7]Note that elasticities in the Ameren and ComEd reports was calculated only using marginal price. We use the sum of marginal price for energy costs and all other average costs in elasticity calculations, since this reflects the prices customers actually pay. Because of this the same reduction in load reflects a lower elasticity in the ComEd and Ameren reports then in ours. We therefore use a wider range of elasticities in our calculations, to reflect the elasticities calculated in these reports, and a higher range for potential increases in elasticity of demand.

– i.e. 5¢/kWh and 6¢/kWh are seen as the same price to a consumer and will not induce behavior change. We use $PT = 10¢/kWh$ and $P_T = 14¢/kWh$ since ComEd customers chose one of these thresholds for high price notifications. We also assume that the ability to shed or shift load is weather dependent, since the major discretionary load for consumers is cooling/heating (Summit Blue, 2007). We assume all customers shift load when temperature exceeds 80°F and space heating customers shift load when temperature is below 30°F. We assume that all ComEd residential customers respond to price, and collectively become price setters, meaning that a reduction in residential demand can reduce LMPs.

Table 3.5: Percent of time that price and temperature thresholds are exceeded.

	Temp < 30°F	Temp > 80°F	All temperatures
Price > 10¢/kWh	1.5%	2.6%	7.2%
Price > 14¢/kWh	0.3%	0.8%	1.6%

3.4.2 Analysis: stable capacity costs

We first assume that consumers are price setters on the energy market but that capacity costs remain constant. We do this to look at the distributional impact due to elastic demand on the energy market alone. Under elastic demand in the long run, supply would readjust (Borenstein, 2005), however we do not include a long-run equilibrium model. Instead we allow elastic demand to move along the actual supply curve for the ComEd node in PJM during 2007 and 2008 (see Appendix E).

The following is done to calculate bill differential when there is an elasticity of demand (more complete details can be found in Appendix F): New hourly consumption for each customer is calculated based on the assumed elasticity of demand, ϵ. The resulting change in system wide demand for the ComEd node of PJM is then calculated. The LMP for that hour is recalculated using a non-parametric regression (Appendix E). Capacity obligations for each customer are calculated based on their new elastic usage. When applicable, new capacity charges are added in. The bills for RTP are then calculated using the new elastic usage, capacity obligation, LMP and capacity charge where applicable. FR bills are re-calculated using the original usages and prices, however we vary capacity in some scenarios to simulate the counterfactual where capacity charges decrease under RTP with respect to FR, due to lower peak demand under RTP. The bills are then differenced in the same manner as in section 3.3.

Figure 3.9 shows the total savings per customer as a function of elasticity of demand, when customers respond to prices above 10¢/kWh and 14¢/kWh. If elasticity is only -0.01 and customers respond when prices exceed 10¢/kWh, then savings amount to only $6/customer-yr, or 0.5% of the average bill. With an elasticity of -0.5 (an upper bound, since this is much greater than the realistic estimates of elasticity under RTP), savings amount to $63/customer-year, or 6% of the annual average bill. The threshold at which customers begin to respond is important. If customers are responding with an elasticity of -0.2 above 14¢/kWh, they can increase savings by over 80% by also responding when prices are 10 - 14¢/kWh.

Despite the fact that there is a net welfare gain for all customers with even the slightest elasticity, not all customers will directly see those savings. Figure 3.9 shows percentage of customers who see a net savings over the year for the scenarios in figure 3.8. It takes an elasticity of -0.2 when customers respond above 10¢/kWh for just half of the customers to see a net savings compared to what they would have paid under FR. With an elasticity of -0.5 (which is likely above the realistic range), only about 60% of customers see a net savings.

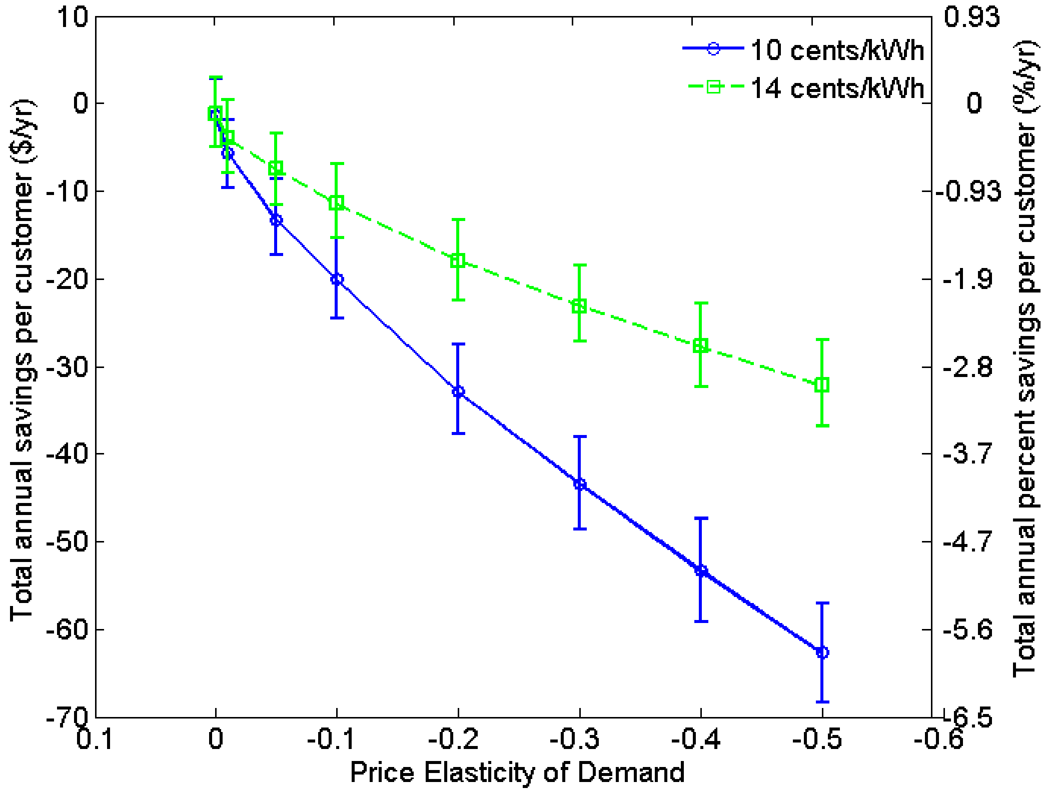

Figure 3.8: Annual savings per customer in both absolute dollars and as a percentage of average bill, as a function of price elasticity of demand, for a price threshold of 10¢/kWh and 14¢/kWh with 95% confidence intervals.

3.4.3 Analysis: increasing capacity cost

We next allow capacity cost to vary under elastic demand. We assume capacity cost to be exogenous and do not include a long-run equilibrium model; we simply explore the distributional effects if capacity were to change by a given amount. We assume two scenarios. In the first scenario, capacity prices increase equally for RTP and FR customers[8]. This is essentially what has happened for customers over the last several years. In early 2007, residential RTP customers in ComEd were paying $0.09/kW-mth for capacity. The capacity price rose to

[8]The capacity charge is rolled into the supply charge for FR customers, so we increase the supply charge to that the total difference paid by all customers is equivalent to the total increase in capacity charge paid by all RTP customers with an elasticity of zero.

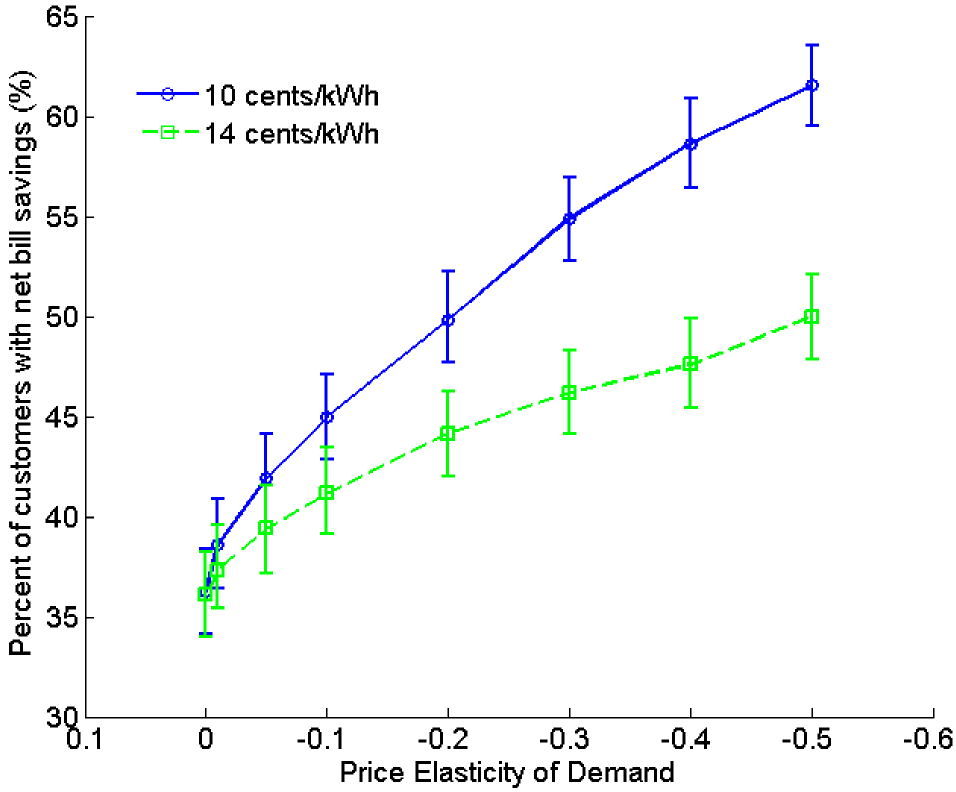

Figure 3.9: Percent of customers who would have a net savings in RTP compared to FR as a function of price elasticity of demand with 95% confidence intervals. The solid curve shows scenarios with a price threshold of 10¢/kWh and the dashed line has a threshold of 14¢/kWh.

$5.70/kW-mth in June 2010, and at the end of 2011 was down to $3.40/kW-mth. In the second scenario, price increases only for FR customers. This is to simulate the counterfactual, where capacity prices would have increased without elastic demand, however the decrease in demand due to the elasticity induced by RTP led to a reduction in necessary capacity and therefore a reduction in capacity prices under RTP.

Figure 3.10 shows the savings per customer per year for these two scenarios, with an assumed elasticity of -0.2 and a price threshold of 10¢/kWh. When capacity increases for RTP customers, and the counterfactual FR customers, RTP customer do save more, but the saving are moderate. A \$5/kW-mth increase in the capacity costs saves roughly an additional \$16/customer-yr, an increase of about 50%. When RTP customers avoid this increase however, marginal savings are significant: the same \$5/kW-mth increase in capacity costs saves an additional \$130/customer-yr, or nearly 400%.

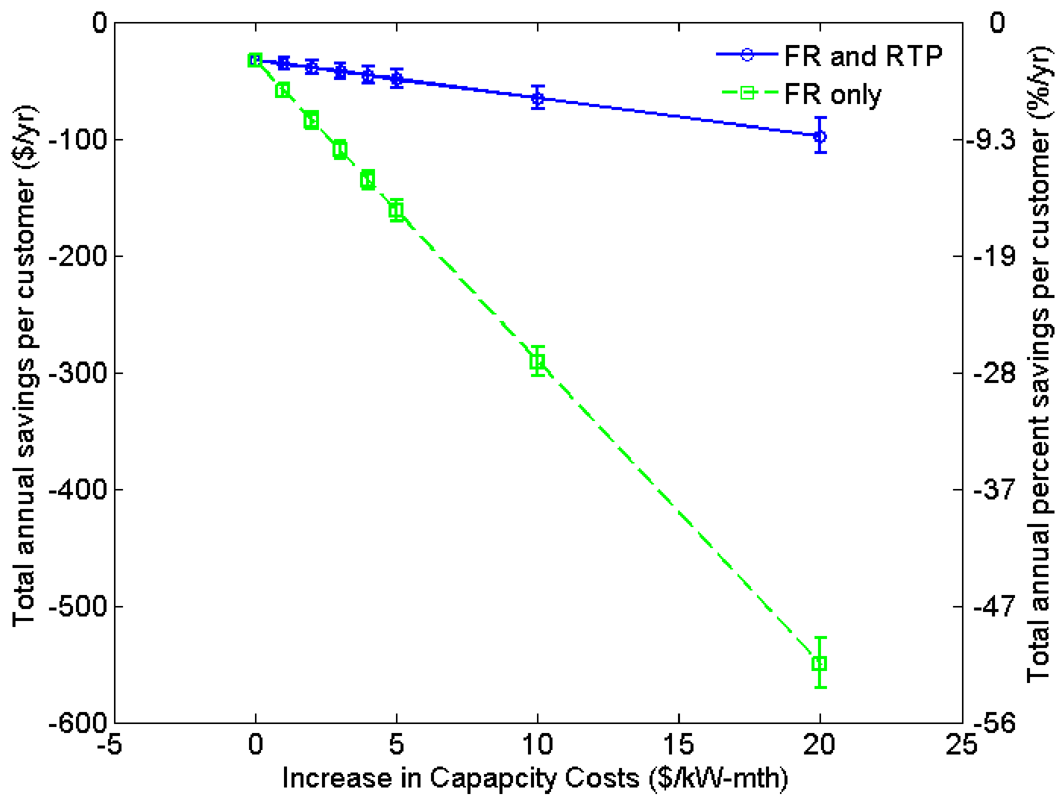

Figure 3.10: Savings per customer per year (absolute and percentage) as a function of increased capacity costs.

Even with additional savings of \$130/customer year, not all customers will directly see the savings. Figure 3.11 shows the percent of customers who save under the scenarios in figure 3.10. With no change in capacity costs, roughly 50% of customers directly save. An increase of \$5/kW-mth results 83% of customers saving – a significant increase, but some customers still faces losses compared to what they would have paid under FR.

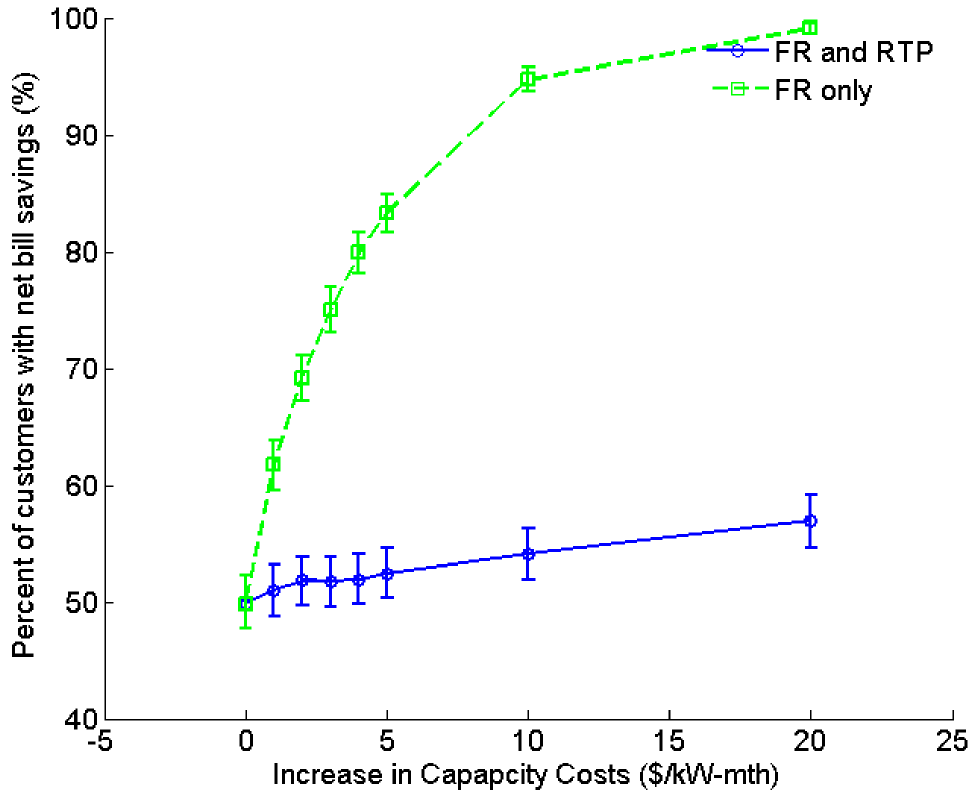

Figure 3.11: Percent of customers who would have a net savings in RTP compared to FR as a function of the increase in capacity costs, for a high temperature threshold of 80°F, low temperature threshold of 30°F and elasticity of demand of -0.2 with 95% confidence intervals. The solid curve represents the scenario where both RTP and FR rates see an increase in capacity costs, the dashed curve shows when only FR sees an increase in capacity costs, but RTP does not.

The patterns of which consumers save, are similar to the patterns in section 3.3. The customers with the largest average usages save the most money, and the customers with the smallest loads lose the most.

3.5 Policy implications and discussion

RTP can bring efficiency to retail electricity markets and has the potential to bring a net welfare increase to consumers if they shift or curtail usage during peak times. However, many consumers will not save money in the short run, even if they have elastic demand from discretionary load, because they would lose the cross-subsidy they receive under FR when switching to RTP. These customers tend to have smaller loads (which may imply less discretionary load, and therefore less elastic demand) and includes a greater proportion of low-income consumers. If there is a mass rollout of RTP, many of these consumers would still lose money in the short run even if they have elastic demand. In the particular case we explored, 50% of customers would still lose money in the short run, even if they had elasticity of -0.2 (which is higher than most estimates of elasticity under RTP).

There is a potential for major savings for all customers in the long run, from avoiding the need to build more capacity. If customers are able to cut peak demand and avoid increased capacity costs in the long run, then many more, or perhaps all customers can save money, however these customers may still see a net bill rise at first.

Policy makers who are considering implementing RTP must not just consider the net efficiency gains and net savings to consumers, but must also look at how these gains will be distributed, and consider that many consumers will actually incur losses relative to FR. Policy makers can consider giving RTP only to the portion of consumers who would contribute the most to peak shaving and will also see direct benefits, however this would be removing a large portion of those who provide the cross-subsidy under FR, pricing, and those being cross-subsidized would still see bill increases. Dynamic rate designs other than RTP, such as

CPP, which focus on only changing prices during the hours when capacity is at the margins, and compensate consumers based on capacity costs only and not energy costs, may be a solution to this issue.

Policy makers also need to focus on how to communicate long run savings to consumers, since RTP can lead to very substantial savings in the long run if significant increases in capacity prices are avoided. This is a huge policy barrier however – it is difficult to tell consumers to bear an increase in electricity bills today to avoid an even larger increase in bills in several years.

The results in this chapter are valid only for customers of ComEd during 2007 and 2008. They are not meant to be directly applied to other jurisdictions or times. We neglected to account for uncertainty in price and demand. It is meant only to serve as a warning to policy makers that a similar analysis is necessary for their jurisdictions before the implementation of a dynamic pricing policy.

Chapter 4

An Econometric Analysis of Real Time Pricing

4.1 Introduction

Demand peaks lead to higher generation costs since some generation will be used for only a few hours each year. In practice utilities keep old, inefficient generators available for these peak hours. Real-time pricing (RTP) has been promoted as a way to reduce peak electricity demand. Replacing a flat tariff that does not vary by hour, season or level of generation cost with real time price should lead customers to reduce their demand as prices rise, thereby lowering costs. In this chapter, we construct an econometric model to analyze 2005 data from the Commonwealth Edison (ComEd) RTP tariff to see if customers are reacting as expected. Section 4.2 describes the ComEd tariff and the data that

*A version of this chapter was submitted to the National Energy Technology Laboratory (NETL) as "Residential Real Time Electricity Pricing: An Analysis of the Illinois Experiment" in August, 2010 by Shira Horowitz, Fallaw Sowell and Lester Lave.

we use. In 4.3 we detail the econometric model we used for the analysis. Results are presented in 4.4 and discussed in 4.6. We briefly compare our analysis to other analyses of the same data set in 4.5.

4.2 Data set

The ComEd Residential Real-Time Pricing Pilot was the first[1] large-scale residential real-time pricing tariff to be offered in the US. It started in 2003 as a joint effort between ComEd and CNT Energy[2]. The program, known as the 'Energy-Smart Pricing Plan' (ESPP) started in January 2003 as a pilot. In January 2007, the real-time tariff became permanent and its name was switched to 'Residential Real-Time Pricing' (RRTP).

From 2003 until mid-2004 when ComEd joined the PJM Interconnection, rates[3] were determined on the basis of the last three years of data from ComEd's commercial RTP program (Summit Blue, 2004). From mid-2004, when ComEd joined PJM, through 2006, rates were determined by PJM day-ahead locational-marginal prices (LMP) for the ComEd node in PJM[4].

In 2007 the program switched from charging customer the day-ahead hourly price, to charging them actual hourly real-time prices (determined by the PJM

[1]Ameren, another Illinois utility began offering an RTP tariff in 2007. PEPCO, started piloting an RTP tariff in the DC area in 2008.

[2]CNT, formerly The Community Energy Cooperative, is a non-profit organization that seeks to help consumers control energy costs.

[3]In addition to the hourly price, customers are charged an access-charge. During the pilot phase, ESPP customers received a 1.4¢/kWh discount off the access charge. During the pilot phase, customers had to be cooperative members of CNT Energy. Any customer could join CNT Energy for a $5 annual fee. During 2003, ESPP was only marketed to cooperative members. From 2004 and on, it was marketed to other ComEd customers, however they still had to join the cooperative to be eligible for ESPP. Since 2007, any ComEd customer can switch to RRTP. It is marketed to customers who are not on electric space-heating tariffs and who have monthly bills exceeding $40. Under RRTP, customers have a reduced meter leasing fee of $2.25/month.

[4]Within PJM the wholesale auction market clear 24 hours in advance; there is also a balancing market in real time.

LMP). Real-time prices for each hour are determined *after* the hour by averaging the 5-minute real-time prices. This means that customers cannot know what they are being charged for the hour until after the hour has been completed. Customers can estimate what they will be charged for the hour, before it occurs by checking the day-ahead prices. Customers can look up prices on a website or call an automated phone service.

Real-time prices frequently depart from day-ahead prices. In the event that five-minute real-time prices are above a certain threshold for 30 consecutive minutes (six five-minute periods) a notification is sent out to participants. Customers can choose a threshold for notification of 10¢/kWh or 14¢/kWh, and can choose to receive notifications via email, SMS (text message) or automated phone call.

Of the data available, we found 2005 to be most likely to show an effect. Customers knew what price they would pay since it was the day ahead price and they could have the chance to plan a response in advance. It was an unusually hot summer with high prices, increasing the potential opportunities for response. However, interpreting the results of the analysis is complicated by the fact that these customers volunteered for the RTP tariff and there is not a good control group who faced a flat tariff. Customers volunteering for an RTP tariff are more likely to take advantage of it than customers who did not volunteer. As shown below, using customers as their own control was adequate. Thus, we believe this analysis is likely to overestimate customer response to RTP.

ComEd, CNT Energy and Comverge supplied a data set that includes hourly usage for the real-time pricing customers as well as flat rate customers. The major part of the data set are described below. Summary statistics for the data are in table 4.1.

Real-time pricing group (RTP) This group consists of single-family households, without electric space heating that were on ESPP or RRTP. In 2003 approximately 650 households were enrolled in ESPP for the full year. As of April 2009, there are 6,350 households. The data consist of hourly usage (kWh) for each household. $Q_{i,t}$ is the electricity usage in kWh for customer i during hour t in the RTP group.

Price The price paid by the RTP group, in ¢/kWh during hour t. The price is the sum of the wholesale price plus a delivery charge. Since the latter is fixed, we analyze only the RTP. P_t is the marginal real-time price paid by the real-time group during hour t.

Temperature The temperature in degrees Fahrenheit. T_t is the temperature during hour t.

Table 4.1: Summary statistics for the data set by year.

	Price (¢/kWh)			Temp. (°F)			Average energy (kWh/h)
Year	Min	Mean	Max	Min	Mean	Max	RTP group
2003	0	3.2	19	-2	51	97	0.92
2004	1	3.8	13	-6	52	92	0.94
2005	0	5.7	20	1	53	104	1.09
2006	0	5.0	37	-6	54	99	0.98
2007	-11	4.9	50	-9	53	93	1.05
2008	-25	5.2	49	-5	50	94	1.12

4.3 Model

In this section we develop an econometric model of customer reaction to the real-time price of electricity. The model described in this section was selected from among several alternative plausible models. The selected model and method of estimation fit the data with residuals whose properties indicated that the model was appropriate for the data. The residuals were distributed as white noise; they were homoscedastic, uncorrelated with the independent variables, and were not serially correlated. Models with other structures that we explored lacked some or all of these properties and could not be considered statistically satisfactory models.

Hourly household electricity demand is a function of weather, activity level and the number and efficiency of household appliances. For customers who are exposed to the real time price, we hypothesize that their demand will also be a function of price. We have no data on activity level or appliances, so they are not included in the model. Instead, we use dummy variables for hour of day to capture the daily variation in demand. As detailed below, weather is modeled as a function of temperature, and activity level by the hour of the day. Temperature and time of day are divided into segments to account for nonlinear effects and we include interaction variables.

The following equation was used to model household demand:

$$\begin{aligned} log(Q_{t,i}) - log(Q_{t-168,i}) = &\sum_{h=0}^{23} \beta_{i,H_{lo,h}} H_{lo,h} + \sum_{h=0}^{23} \beta_{i,H_{hi,h}} H_{hi,h} \\ &+ \beta_{i,P_{lo}} P_{lo,t} + \beta_{i,P_{hi}} P_{hi,t} + \beta_{i,T_{lo}} T_{lo,t} + \beta_{i,T_{hi}} T_{hi,t} + \beta_{i,T_{hi}^2} T_{hi,t}^2 + \nu_t \end{aligned}$$

where:

$Q_{i,t}$ is electricity consumption of customer i during hour t in kWh/h,

T_t is temperature during hour t in degrees Fahrenheit,

P_t is real-time price during hour t in ¢/kWh,

$T_{lo,t} = I(T_t < 60)(T_t - 60)$,

$T_{hi,t} = I(60 \leq T_t)(T_t - 60)$,

$P_{lo,t} = I(T_t < 90)P_t$,

$P_{hi,t} = I(90 \leq T_t)P_t$,

H_h Dummy variable for hour of the day, $h \in \{0, 1...23\}$,

$H_{lo,h} = H_h I(T_t < 60)$,

$H_{hi,h} = H_h I(60 \leq T_t)$,

and all parameters are denoted by $\beta_{i,X}$, where X is the variable it is a coefficient to in the model and i denotes the customer. Note that $I(X)$ is an indicator function that is 1 when X is true and 0 when X is false.

A log transformation was performed on demand, $Q_{i,t}$, for the residuals to have the statistical properties of white noise. $log(Q_{i,t})$ was differenced to achieve stationarity. A lag of 168 was used in differencing, since $t - 168$ is the same time of day, one week prior, to time t. We chose to use a week prior instead of 24 hours prior to time t, since demand profiles are different on weekdays and weekends.

Temperature was included in the model with the variables: $T_{lo,t}, T_{hi,t}$ and $T^2_{hi,t}$. The structure included three variables to account for different behavior in winter, summer and extremely high temperatures. The cutoff between $T_{lo,t}$ and $T_{hi,t}$ is 60°F. 60°F was chosen since demand is roughly linear with respect to temperature above and below 60°F, with a break at 60°F.

We do not have data on household appliances or activity levels (e.g. size of household, when household members are home, etc.), however, electricity usage tends to follow a daily and seasonal pattern. We use dummy variables for hour of day to capture the daily variation in demand. There are two sets of hourly dummy variables, one for temperatures above 60°F and one for temperatures below since the intercept terms are different for the summer and winter.

A residual analysis revealed that price needed to be split into two variables – one for price at extremely high temperatures, $P_{hi,t}$, and one for the remainder of prices, $P_{lo,t}$. 90°F was used as the cutoff point. This is because customers tend to have more discretionary load that is easy to shed at higher temperatures (i.e. air conditioners), and can therefore react to price differently.

Each household has a distinct load profile and will react differently to price, so we estimate the parameters for each household individually using a random effects model.

The data used to estimate the model for each customer are a time series, which result in serial correlation of the error term ν_t under ordinary least squares regression (OLS). Serial correlation leads to biased estimates for the standard errors of the β_x coefficients. In order to correct for the autocorrelation, the error term was modeled as:

$$\nu_t = \epsilon_t - \sum_{x \in A} \delta_x \nu_{t-x} \tag{4.1}$$

where:

the ϵ_t are independently and identically distributed $Normal(0, \sigma^2)$,

σ^2 is constant, and

$A = \{1, 24, 168\}$.

Lag terms of 1, 24 and 168 were used to take care of the autocorrelation at the hourly, daily and weekly cycles.

4.4 Results

Maximum likelihood estimation using the Autoreg procedure in SAS was used to estimate the model described above. The model was estimated for the 481 customers on real time pricing who had complete data for 2005 (i.e. data for every single hour with no outliers).

2005 was the hottest year (see table 4.1) for which we have data. Since an air conditioner can be the highest load in the residence, we reasoned that the combination of the high prices during these hours and the ability to turn up or turn off the air conditioner would provide the clearest signal of customer reaction to high price. Since these hours provided the greatest incentive (highest price) to reduce demand and the simplest way to reduce demand (reduce the air conditioner load), we hypothesized that if we could not find an identifiable reaction here, we were unlikely to find it in other years.

While the statistical estimates associated demand changes to higher prices in some customers, the associated change was not always as predicted. Some customers reduced their demand while others increased their demand. Since we reject the suggestion that customers react to high prices by increasing demand, we assume that the model was unable to control completely for the effect of high temperatures in increasing the demand for air conditioning. In this model, each customer was her own control, using data from the previous week and measuring temperature directly. Perhaps if there had been controls consisting of customers whose hourly usage was measured but who faced a flat tariff, the model would have been better able to hold other factors constant.

The unexpected results are summarized in figures 4.1 and 4.2. Figure 4.1 shows the distribution of t-statistics for the parameter estimates $\beta_{i,P_{hi,t}}$. A t-statistic greater than 2 in magnitude means that we can reject the null hypothesis that $\beta_{i,P_{hi,t}} = 0$ at the 95% confidence level. If this null hypothesis were true, it would imply that price at high temperature, $P_{hi,t}$, has no effect on demand, $Q_{i,t}$. That is, we would have no signal to indicate that customers are price responsive when temperature is high. T-statistics that are positive indicate positive responses to $P_{hi,t}$ (i.e. customers increase usage as price increases), while negative t-statistics imply the expected negative responses.

Figure 4.2 shows the distribution of t-statistics for the parameter estimates $\beta_{i,P_{hi,t}}$. The implications of this figure are the same as for figure 4.1, but for price at low temperature, $P_{lo,t}$, instead.

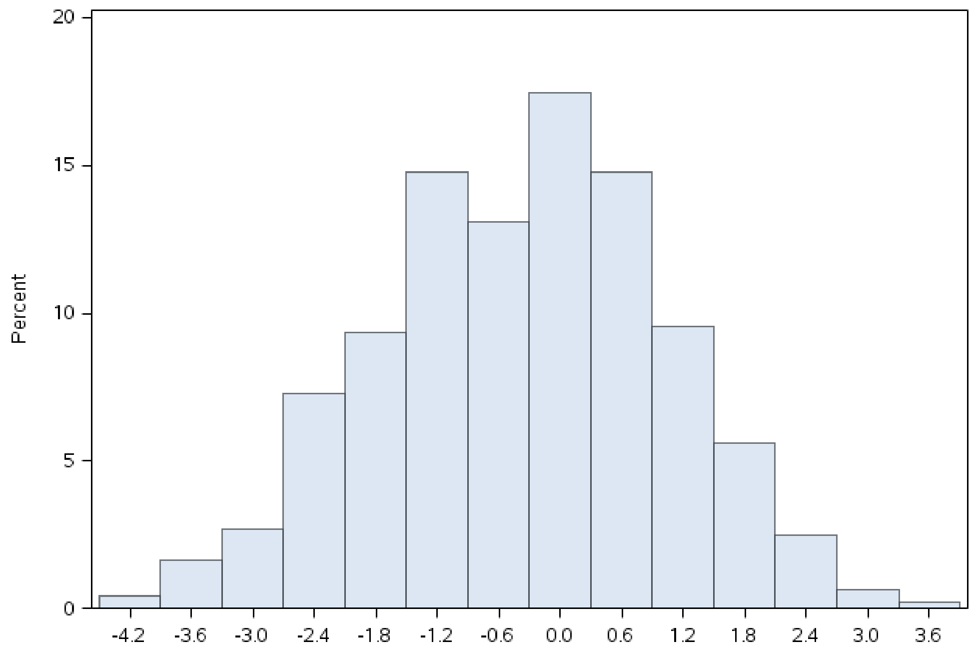

Figure 4.1: Histogram of t-statistics for $\hat{\beta}_{i,P_{hi,t}}$

Both figures show that only a small fraction of customers, less than 15%, have t-statistics that are both significant and negative at the 95% confidence level. This means that 85% of customers did not reduce electricity use systematically or increased electricity use when price rose. The two figures show that about as many customers increased usage at high price as reduced usage at high price. Since we reject the notion that customers increase usage due to high price, the two figures indicate no clear evidence that customers are reacting as expected.

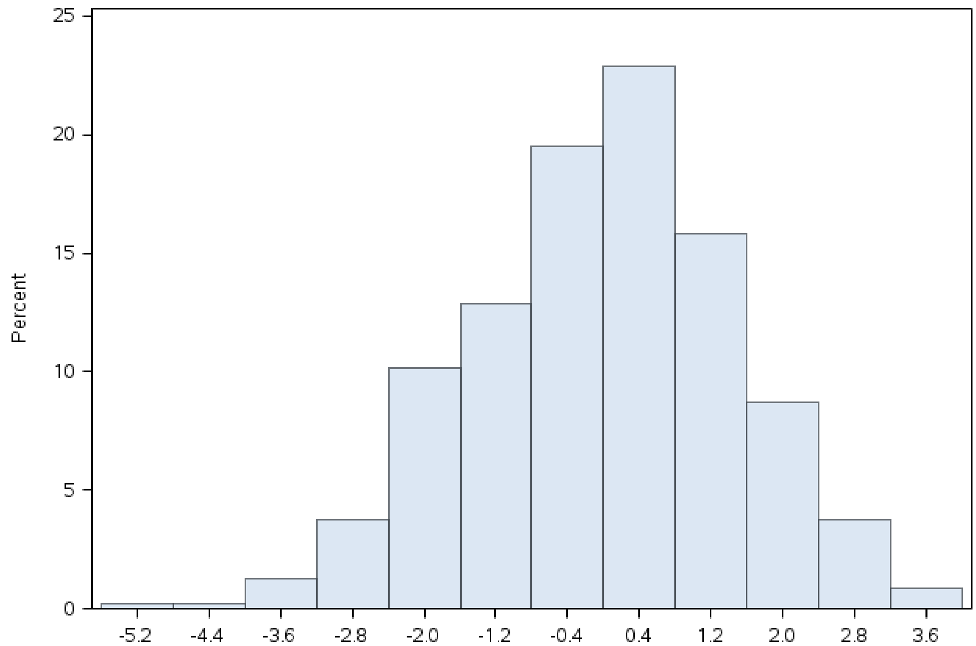

Figure 4.2: Histogram of t-statistics for $\hat{\beta}_{i,P_{lo,t}}$

4.5 Literature review

There have been two other analyses of this RTP data to our knowledge. Summit Blue (2004, 2005, 2006, 2007) analyzed the data from 2003 - 2006 and Allcott (2011) of MIT analyzed the 2003 data.

Both Summit Blue and Allcott found a statistically significant response to RTP, while we did not. Table 4.2 summarizes the results of the other analyses. We cannot comment on the validity of their models without additional information, specifically a careful examination of the residuals from their fitted models. We can only be sure that our residual analysis indicates that our statistics are valid. In this section we will point out some of the limitations of the other analyses and suggest reasons that their results differ from ours. It should be noted that to our knowledge, none of the analyses (including this one) have been peer reviewed.

Allcott's analysis was only of the 2003 data, while we only examined the 2005 data. We chose to start with the 2005 data since it was the hottest summer

Table 4.2: Results of other analyses (Summit Blue, 2004, 2005, 2006, 2007; Allcott, 2011)

Author	Year	Elasticity	
Allcott	2003	-0.1	
Summit Blue	2003	-0.042	
Summit Blue	2004	-0.080	
Summit Blue	2005	-0.047	
Summit Blue	2006	-0.047	(< 13¢/kWh)
		-0.082	(> 13¢/kWh)

for which we have available data, and had persistently high prices. Since air conditioners are the largest discretionary load that customers were shifting, we hypothesize that if we cannot find a signal in 2005, there is likely no signal in other years. Allcott chose the 2003 data since it has a representative control group. We decided not to start with 2003, despite the control group, because we suspected errors in the data for the early portion of the year (January - April), and wanted to start with a full year of data to analyze (Allcott used only data from May and on). It is possible that there was a response in 2003 that declined in 2005 either because the population changed or because the responsiveness declines over time.

Alcott is modeling a different effect than we did. Alcott compares the consumption of the RTP group to the consumption of the control group, so he is detecting general conservation as well. For example, if a customer on RTP purchases a more efficient air conditioner, it will appear as if he is responding to price, when in fact it is just an artifact of the more efficient appliance and not a direct response to price. It is possible that some customers were motivated by RTP to acquire more efficient appliances, however customers recruited for this program were already more likely to have more efficient appliances (Summit Blue, 2004). While the control group is representative of the RTP group for 2003, the RTP group received education about energy efficiency that the control group did not, which may have influenced appliance purchasing. We modeled only direct, short-term response to price, and therefore would have missed out on any responses that are a result of efficiency increases.

Summit Blue found a statistically significant response in all four years it analyzed. We dismiss their 2003 analysis since they failed to account for auto-correlation and heteroscedasticity. The data are highly serially correlated, so Summit Blue's t-statistics for 2003 are invalid.

Some of the results of Summit Blue's 2003 and 2004 analysis contradict each other. For example, the 2003 analysis shows a decrease in consumption during high price alerts, while the 2004 analysis shows either an increase in consumption or no change in consumption during high price alerts. 2003 shows higher elasticities for multi-family than single-family homes, while 2004 shows the opposite. While this may in fact be what happened, it also may be indicative of model misspecification or inaccurate t-statistics.

Summit Blue also restructures its model several times, which calls to question the accuracy of its earlier models. Some of the changes are: switching from a linear to a log-log model; splitting price up by time of day; adding dummy variables for high price notification during the day; and adding dummy variables for high price notification during the afternoon and evening.

Both Allcott and Summit Blue included high price alerts. We did not find any statistical significance when including the high price alerts in our model, and therefore did not include them in our final model.

4.6 Discussion

The results of this analysis do not indicate that customers systematically reduce electricity use as price increases. A small response might be hidden within the random variation in use that occurs from hour to hour. However, the analysis does indicate that this group of customers, more likely to react to higher prices because they opted in to the experiment, did not display reactions to price that would allow ComEd to plan to reduce their peaking capacity.

There are several explanations for why we could not extract a signal. Prices did not fluctuate very widely during 2005, ranging only from 0 - 20¢. Prices were greater than 15¢ during only 1% of the year. If a customer were to shed 1 kWh for the most expensive 1% of hours, he would only save about $15 over the entire year. Even though 2005 was an unusually hot year, temperature was above 90°F for less than 1% of the year. This gave customers little opportunity to shed air conditioner load.

Being able to compare the RTP group with a representative control group would make it easier to extract a price signal if there is one. It would allow us to more accurately answer the question: "how much power would this customer have used has he not been exposed to real-time price?", so we could have a higher signal to noise ratio. Larger price fluctuations would also make it easier to extract a signal. However by comparing a customer's electricity use during periods of high prices, with previous and accounting for systematic daily and hourly demand, we believe we have adequate, although not optimal, controls.

Real-time pricing pilots and tariffs are expensive to carry out. We recommend that future pilots secure customers who are not volunteers, that they have a comparable control group of customers (whose hourly usage is recorded even though they face a flat tariff), and that customers have more readily available information about expected and current price during each hour and have a device that enables them to reduce their demand in response to rising prices with less effort.

Chapter 5

Forecasting & Measurement for Direct Load Control

5.1 Introduction

Independent system operators (ISOs) and electrical utilities implement demand response to alter electricity consumption in order to maintain grid reliability or provide electrical service at a lower cost. One approach is direct load control (DLC) where electrical appliances are remotely powered off. Air conditioners (ACs) are used in DLC where a load aggregator[1] controls many ACs. In restructured (or competitive) electricity markets, the load aggregator can then bid this

*A version of this chapter was submitted to the Journal of Applied Econometrics as "Forecasting, Measurment and Verification for Direct Load Control in Energy Markets" by Shira Horowitz, Brandon Mauch and Fallaw Sowell. Collaborative research in the Department of Engineering & Public Policy is the norm. This chapter is based on work done in close collaboration between Shira Horowitz and Brandon Mauch.

[1] A load-aggregator can be a load serving entity such as a utility or it can be an independent aggregator.

load reduction into many of the same markets that suppliers can bid conventional generation into, such as the energy and capacity markets.

Unlike traditional generation where the supply is deterministic (barring events that lead to a forced outage), the available DLC resource is uncertain and must be forecasted. While generators are paid according to the quantity of energy supplied, DLC participants are paid based on the amount of load reduction[2]. Load reductions cannot be directly measured; they are estimated by subtracting actual load during a DLC event from the amount of load a customer was assumed to have without the DLC event. In this chapter we propose a new method for forecasting and measuring DLC of residential ACs using a Tobit model with both upper and lower censoring.

5.1.1 Residential Direct Load Control

Although DLC has been used since 1934 (Fanney and Dougherty, 1996), electric utilities began widespread implementation of demand response and energy efficiency programs in the 1970s in response to increased fuel prices and growing demand for electricity. Electric demand grew 35% from 1991 to 2011 (EIA, 2012a). To satisfy demand growth, electric power providers must build more power plants and transmission lines which are costly and take years to build. Effective DLC programs allow system planners to delay construction of new power plants or transmission lines by shifting peak demand to other times. DLC is also used in some regions to provide reserve capacity for contingencies in the grid. This allows grid operators to schedule less conventional generation for reserves.

[2]DLC in the capacity market typically settles based on firm contracts, while DLC in energy markets usually settles based on market prices. Load aggregator and large customers receive the market prices, however residential customers usually receive a flat rate for participation.

In residential DLC programs load aggregators remotely turn off appliances. Several appliances are used for DLC such as ACs, water heaters and pool pumps. We focus on DLC applied to ACs. Direct control of residential ACs began in the 1970s to reduce peak demand (Flanigan and Hadley, 1994). ACs are "cycled" by switching off the compressor for short periods of time during a DLC event. ACs are well suited for DLC since they comprise a large portion of residential loads (roughly 20% of residential electricity consumption) (EIA, 2012b), and are often at their peak use during afternoons when electricity prices are high (Reddy et al., 1992; Sastry et al., 2010). Also, unlike many appliances such as lights and computers, air conditioners can be powered off for a brief time without much discomfort felt by customers. An early investigation of comfort levels during DLC events showed that only 15% of participants reported discomfort during the events (Kempton et al., 1992). A California utility surveyed customers during a pilot study and found the majority did not notice DLC events lasting 15 minutes or less (Sullivan et al., 2012). Other studies of AC load control programs indicate 10 to 30% of customers override the control signal after 2 hours of control depending on the ambient temperature (Kema, 2006; Kirby, 2003).

Advanced electric meters (i.e. smart meters) enable greater use of DLC in electric grids (Strbac, 2008; Hamilton and Gulhar, 2010). DLC for residential ACs is currently accomplished via wireless signals sent to appliances. Communication occurs in one direction, so there is no ability to verify if an appliance responded to the signal. Advanced meters will alleviate this issue by providing two-way communication. They will also allow the collection of load data at time intervals of one hour or less, allowing better load reduction verification and greatly increasing the ability to forecast loads. The Federal Energy Regulatory Commission's (FERC) 2011 report on demand response and advanced metering showed the penetration of advanced meters increased from 8.7 to 13.4% of all electricity customers from 2009 to 2011 (FERC, 2011a). Federal spending on advanced metering initiatives from the American Recovery and Reinvestment Act is driving this growth which the Edison Foundation's Institute for Energy Efficiency projects to reach over 50% by 2015 (DOE, 2012).

Recent changes in wholesale electric markets are also likely to increase the use of DLC. In 2011, FERC issued order number 745 which directs wholesale energy market operators to compensate demand side resources the full energy market price as long as dispatching the DR resource is cost-effective (FERC, 2011b). Each market operator sets a threshold price based on historical data which is used as the minimum price at which DR resources are compensated for load curtailments.

DLC provides flexibility in the grid that may enable greater use of wind and solar power (Callaway, 2009; Koch et al., 2010). These renewable sources of energy have environmental benefits, but their variable generation presents challenges to grid operators. DLC resources can quickly respond to drops and increases in wind or solar output in a manner that is potentially more cost effective and reliable than dispatching an additional generator (Newell and Felder, 2007). Increased reliance on electricity generation from wind and solar power is one factor that may drive DR programs (DOE, 2008). This will require more accurate load forecasting techniques that are easy to implement, like the method we develop in this work.

5.1.2 Load Forecasting

Accurate load forecasts for DLC events are essential for many reasons. DR resources are paid the energy market locational marginal price for the amount of load reduced based upon the customer baseline (CBL), an estimate of the counterfactual event of energy use without a load reduction. Inaccuracies in the CBL lead to incorrect and unfair payments. Underpayments for DR resources discourage further participation while overpayments lead to excessive charges levied on load serving entities who must pay for the reductions. System planners need to accurately know how much load reduction to expect during a system emergency. As DLC programs grow, uncertainty in the load forecasts will become a bigger issue, especially as DLC resources provide more ancillary services.

A review of literature from independent system operators (ISOs) and regional transmission operators (RTOs) shows that default CBLs differ greatly across markets (Grimm, 2008; Kema, 2011). Most of the CBLs are simple moving averages. All ISO/RTOs accept alternative methods for CBL determination as long as it is approved. In the PJM RTO, the default CBL is the average hourly load profile from the 4 highest load days of the previous 5 similar day types (weekdays, Saturdays, Sundays/holidays) (PJM, 2012). The California ISO calculates CBLs by averaging loads from the previous 10 similar days (CASIO, 2012). The New York ISO uses an average of 10 similar day types (NYISO, 2010). New England's ISO also uses ten similar day types for the CBL (ISONE, 2012). The Electric Reliability Council of Texas publishes 3 different default CBL calculations: a linear regression of energy consumption on covariates representing weather conditions, daylight hours, season and day of the week; a moving average of 8 of the previous 10 similar days; or a model that averages days with load profiles similar to the event day (ERCOT, 2012). The Midwest ISO does not implement a default CBL and asks participants to submit their own forecasts for approval (Newell and Hajos, 2010). All ISO/RTOs allow for intercept adjustments to the CBL to better align it with load on the day of the event. This improves the accuracy of verifications (Kema, 2011; Coughlin et al., 2009; Goldberg, 2010).

Moving averages do not produce a good forecast for highly variable loads like residential ACs, so there is substantial work on air conditioner load forecast models. Broadly speaking, the models can be classified into two distinct categories: physical models and statistical models. Both model types attempt to forecast AC load as a function of several variables, primarily: temperature, time of day and relative humidity.

Most of the work in this area is directed at developing physical models of houses by employing an energy balance on a residence to estimate heat flow from the ambient air into the living space. These models consist of a system of differential equations that describe the evolution of indoor temperature and the on/off cycles of the air conditioner compressor given weather variables such as temperature, relative humidity, solar radiation, etc. Implementation of these models requires knowledge of thermal characteristics and thermostat settings of each house for use as parameters (Bargiotas and Birdwell, 1988; Molina et al., 2003; Gustafson et al., 1993). Parameters can be measured at each house, but a more common approach is to use maximum likelihood algorithms to estimate the parameters from historical data (Pahwa and Brice, 1985; El-Ferik et al., 2006; Kamoun and Malhamé, 1992). The latter method still requires knowledge of the thermostat setpoints. Once a single residential AC is adequately described, it is used to produce a forecast of aggregate demand from many ACs. Several methods to aggregate individual AC loads have been proposed in the research community (Molina-García et al., 2011; Malhamé and Chong, 1985; Callaway, 2009). Usually this is carried out by expressing one or more variables with a probability density (i.e. indoor temperature or on/off state of compressors). This class of models is very expensive to implement because they require large quantities of data. They may also be sensitive to changes in the physical properties of the residence. Finally, they do not capture the behavioral aspects of AC use such as work schedules of occupants at the residence.

Statistical models on the other hand do not directly model the dynamics of energy flows. Instead they capture trends in historical AC load data to predict future loads. There is comparatively less work on statistical models applied to AC load forecasts, especially residential AC loads. One proposal to forecast load reduction from AC DLC relied on fitting a model to load measurements at a feeder circuit level (Eto et al., 2012). This method cannot forecast load for individual households. It also requires that a large fraction of ACs on each feeder participate in DLC so that it can distinguish the signal from the noise.

Parametric models of AC duty cycles have also been used to estimate load reductions by comparing controlled and non-controlled AC data (Ryan et al., 1989). Autoregressive models have also been used in AC forecasts for non-residential buildings (Penya et al., 2011), but they would not likely fit highly variable residential data well. Finally, more advanced models have been proposed to forecast building energy consumption using support vector regression (Xuemei et al., 2010) and artificial neural networks (Beccali et al., 2004). These types of models capture the non-linearities in energy demand, but are very data intensive for each household.

Given that all ISO/RTOs currently implement simple statistical models to forecast loads, a straightforward econometric method to forecast AC load for DLC applications seems likely to gain traction. We apply a doubly censored Tobit model to forecast hourly individual air conditioner loads. This accounts for the non-linearities inherent in AC energy consumption while not requiring extreme amounts of data. Our model uses ambient temperature and time of day as covariates to estimate air conditioner use. The individual loads are aggregated via a bootstrap method to create an aggregate load forecast with confidence intervals. Using this approach we calculate day-ahead hourly load forecasts over a 30 day period for a group of 467 air conditioners. Temperature values for the following day are assumed to be known ahead of time. Forecast models are recalibrated each day with the data available at the time of the forecast.

The remainder of this chapter is organized as follows: in section 5.2 we describe the dataset. Section 5.3 describes the Tobit model and the theoretical framework of the model. The results are in section 5.4 and section 5.5 covers the policy implications of this work.

5.2 Data

We obtained, under a confidentiality agreement, a dataset from Pepco Holdings, Inc. The dataset contains AC energy consumption data, weather data and metadata for the ACs for 536 residential ACs from July - September 2010. Due to various issues with data quality we discarded data from 69 units and analyzed data from the remaining 467 units (details on data quality and cleaning protocol are in appendix G.1). Data loggers were installed on the air conditioners during the month of July so the initial date of data collection varies. Nearly all loggers provided data for the entire months of August and September. The data loggers recorded current measurements for the compressor circuits. During installation, technicians took spot measurements of voltage and power which were used to convert the current measurements to power measurements.

The raw data were instantaneous power values recorded at three minute intervals. We assumed a constant power level during each three minute period to estimate energy consumption at the hourly time scale. In other words, the compressor was assumed to either be on or off for the entirety of each 3 minute period. In adding up the energy consumed during each of the three minute periods during an hour, the hourly estimates take on 20 discrete values. These errors will not have a significant effect on the final results which are aggregated over all units. We also simplified the data by using the rated power level of the compressor during intervals it was running and zero values when it was off. The raw data showed power values fluctuating mildly around the rated power level of the compressor while it was running.

Air conditioners in this study were located in service territories for three different utilities: Potomac Electric Power Company (PEPCO), Delmarva Power and Light (Delmarva) and Atlantic City Electric (ACE). Figure 5.1 shows the region covered by these utilities. PEPCO's Washington D.C. customers and Delmarva's Delaware customers were not included. Hourly temperature and humidity data were collected from weather stations located near each utility's territory and were assumed to be uniform throughout each region. Temperature statistics for each region during the time period covered in the data are in table 5.1. Temperature data for ACE had three missing values out of over 2100 observations, two of which were during consecutive hours. We interpolated them from the adjacent hours.

Table 5.1: Temperature data statistics during the period July - September 2010 from each region where the air conditioners are located.

	Utility		
	PEPCO	ACE	Delmarva
Minimum temperature (°F)	57	49	54
Maximum temperature	98	99	96
Mean temperature	76	73	74
Standard deviation	7	9	8

Many ACs included in the dataset belong to customers who participate in a DLC program that cycled air conditioners during periods of extremely high demand. In order to participate in the DLC program, customers agreed to have either switches capable of remote operation installed on the AC compressor circuit

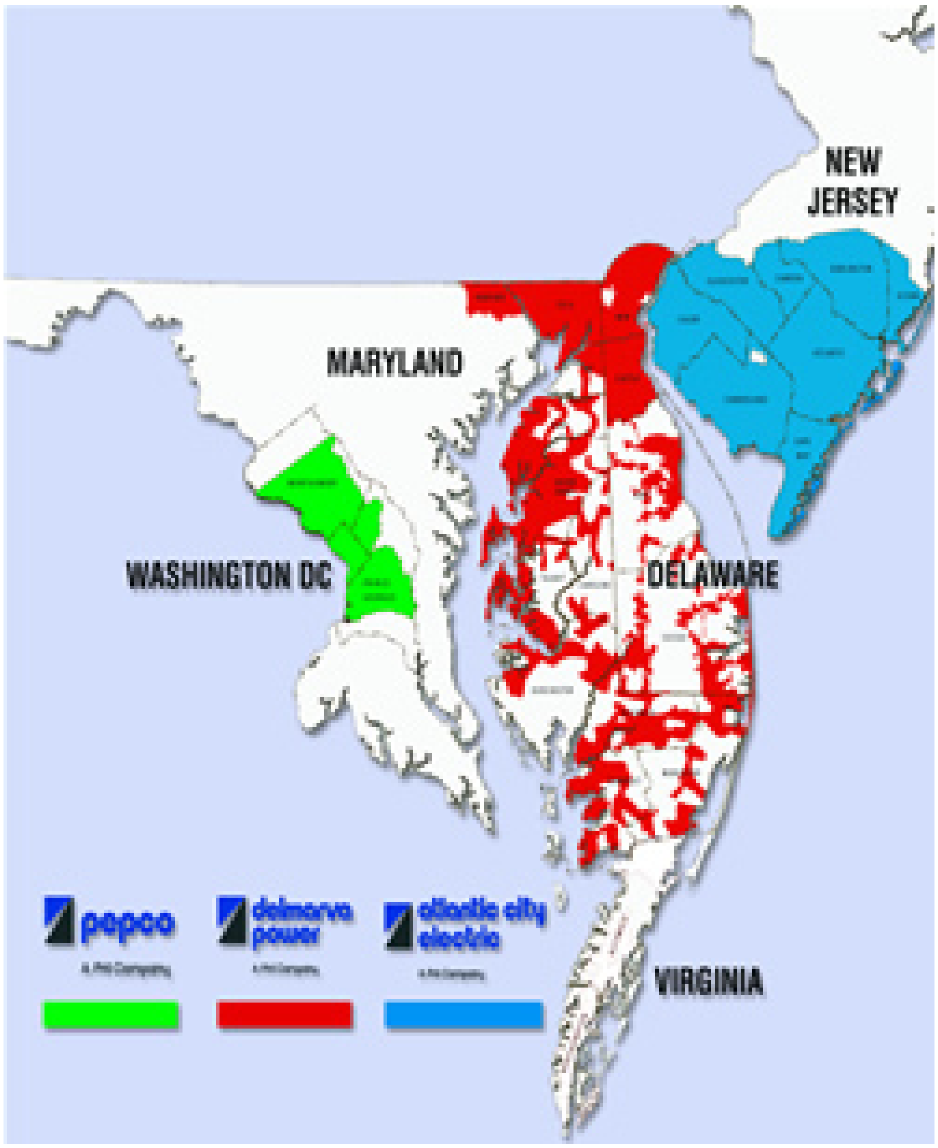

Figure 5.1: Map of the regions served by the three utilities where the data were collected (PHI, 2012).

or smart thermostats that could be adjusted remotely. Signals indicating a DLC event were sent through a pager network. Customers received notice 24 hours prior to a DLC event. During the time period covered in the data, 8 DLC events occurred ranging in duration from one to four hours. Customers had the option of overriding the signal if they wanted. However, this only occurred with one customer in the dataset.

Customers in the DLC program were on one of three cycling levels: 50%, 75% or 100%. Air conditioner control during a DLC event used a smart algorithm to limit the time a compressor could run. Summary statistics for the dataset are in table 5.2.

Table 5.2: Summary statistics from AC data set.

Variables	PEPCO	Utility ACE	Delmarva	Total
Number of total air conditioners	181	72	214	467
Air conditioners cycling at 50%	58	72	88	218
Air conditioners cycling at 75%	68	0	68	136
Air conditioners cycling at 100%	55	0	58	113
Air conditioner size < 2 kW	50	10	49	109
Air conditioner size ≥ 2 and < 3 kW	83	42	110	235
Air conditioner size ≥ 3 and < 4 kW	36	17	50	103
Air conditioner size ≥ 4 kW	12	3	5	20
Average air conditioner size	2.6	2.7	2.5	2.5
Air conditioner age ≤ 5 yrs	56	30	70	156
Air conditioner age > 5 and ≤ 10	61	12	79	152
Air conditioner age > 10 and ≤ 15	39	17	46	102
Air conditioner age > 15	25	13	19	57
Average air conditioner age	9.1	9.5	8.6	8.9

5.3 Framework

5.3.1 Tobit Model

Preference for AC usage is positively related to temperature. At higher temperatures, consumers want more cooling, even if their AC has reached is maximum capacity, while at cooler temperatures, consumers want less AC, and if it is cold enough, they may even want a negative amount of AC (i.e. heat). Actual AC load however, is constrained by the capacity of the AC: it can never be less than zero and cannot exceed the maximum AC capacity. We therefore model observed AC energy consumption using a doubly censored regression model, also known as a Tobit model (Tobin, 1958).

We model each AC individually and add the results for an aggregate forecast. Preference for AC i at time t (incremented hourly) is modeled as a latent variable y_i^*:

$$y_{i,t}^* = \sum_{h=1}^{24} (\beta_{D_h,i} D_{h,t} + \beta_{TD_h,i} D_{h,t} T_t) + \beta_{T^2,i} T_t^2 + \beta_{T1,i} T_{t-1} + \beta_{E,i} E_t + \beta_{P,i} P_t + \epsilon_{i,t} \tag{5.1}$$

where T_t is $max(0, R_t - 65)$, R_t is the temperature in degrees Fahrenheit during hour t, $D_{h,t}$ is an indicator variable for hour of the day, E_t, an indicator variable for a DLC event during hour t, P_t is an indicator for the three hours immediately after an event and $\beta_{\chi,i}$ is a parameter for AC i for covariate χ. The error $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma_i)$, where $\mathcal{N}$ represents a normal distribution, accounts for unobservables and random shock.

The shifted temperature term and temperature squared account for non-linearities of the observed temperature range. We use indicator variables for the 24 hours of the day and have an interaction variable with the indicators and temperature to account for consumers' diurnal activity cycle which affects preference for AC. The lagged temperature term is included to account for thermal inertia in homes. Only a lag of 1 was included because the partial-autocorrelation function was insignificant beyond a lag of 1.

Certain ACs had one or more hours of the day that had very few uncensored $y_{i,t}$ values (i.e. all the values at 3 a.m. for a particular AC were either 0 or λ_i, the capacity of the AC). This makes it difficult for the optimization routine to converge and results in insignificant estimates. We therefore combined any $D_{h,t}$ with 3 or fewer uncensored values with $D_{h-1,t}$ or $D_{h+1,t}$ (which ever had fewer uncensored values) until each $D_{h,t}$ contains greater than 3 uncensored values.

Consumers do not have a preference for DLC events, however there were DLC events in the dataset so they are accounted for with E_t. A DLC event may increase a customer's preference for AC immediately after the event, since her AC may have cycled when she would have preferred it to be on, so P_t is included to account for this. Data for event and post-event hours had to be included in the analysis because the heteroscedasticity and autocorrelation consistent standard errors require regularly spaced data (see appendix G.2).

We explored additional variables such as lagged AC load, humidity and cooling degree hours, however these variables were all strongly collinear with other covariates and were rejected for this model.

To simplify the notation, we combine all covariates into vector $\boldsymbol{X_t}$ and all $\beta_{\chi,i}$ in vector $\boldsymbol{\beta_i}$ and rewrite (5.1) as:

$$y^*_{i,t} = \boldsymbol{X_t}'\boldsymbol{\beta_i} + \epsilon_{i,t}. \tag{5.2}$$

We censor $y^*_{i,t}$ between 0 and λ_i, the capacity of the AC, to obtain $y_{i,t}$, the actual energy consumption of AC i during hour t:

$$y_{i,t} = \begin{cases} 0 & y^*_{i,t} \leq 0 \\ y^*_{i,t} & 0 < y^*_{i,t} < \lambda_i \\ \lambda_i & \lambda_i \leq y^*_{i,t}. \end{cases} \tag{5.3}$$

We estimate $\boldsymbol{\beta_i}$, as $\hat{\boldsymbol{\beta}}_{\boldsymbol{i}}$ using maximum-likelihood estimation. The likelihood function is in appendix G.2.

Serial correlation of the errors is accounted for with heteroscedasticity and autocorrelation consistent (HAC) standard errors. HAC standard errors using White standard errors and Newey-West covariance weights are derived in appendix G.2 using Bernard and Busse (2003). We do not use generalized least-squares to obtain consistent estimates for $\hat{\boldsymbol{\beta}}_{\boldsymbol{i}}$ because of difficulties analytically specifying the likelihood function.

5.3.2 Forecasting and Confidence Intervals

The model described in 5.3.1 was used to forecast AC load for each customer. Individual forecasts were summed to forecast an aggregate load. A load-aggregator would typically bid DLC into the forward energy market the day before the event is to occur. For example, a load aggregator would place a bid in the forward market on August 14 for a DLC event that is to occur on August 15. The aggregator would have data up to and including August 13 to forecast load for the August 15 event. Our forecasts are computed the same way. For an August 15 forecast, we compute the parameters with all the data up to and including August 13. For an August 16 forecast we use all data up to and including August 14. Each AC,

i therefore has different parameters $\hat{\boldsymbol{\beta}}_{\boldsymbol{i,d}}$ for each day d. In general, $\hat{\boldsymbol{\beta}}_{\boldsymbol{i,d}}$ and $\hat{\sigma}_{i,d}$ are estimated using all available $X_{i,t}$ where $t < d-2$.

The starting values used for the parameters maximum likelihood estimate for the first day are the ordinary least squares estimates. The starting values for each successive day $d > 1$ are the estimates from the previous day: $\hat{\boldsymbol{\beta}}_{\boldsymbol{i,d-1}}$ and $\hat{\sigma}_{i,d-1}$. Results were not sensitive to changes in the starting values.

We include uncertainty associated with $\sigma_{i,d}$, the variance of the error term, in our forecast and confidence intervals. The bootstrap method is necessary to compute aggregate forecasts and confidence intervals because of the non-linearities created by censoring. The latent residuals are Gaussian, however the censored residual are not. There is a high degree of asymmetry in the residuals since there are many more observed low temperatures than high temperatures. We used $M = 1000$ iterations of the bootstrap. Results were stable beyond 1000 iterations.

The forecasted latent variable estimate for customer i at time t on day d is:

$$\hat{y}^{*}_{i,t} = \boldsymbol{X_t}'\hat{\boldsymbol{\beta}}_{\boldsymbol{i,d}} \;\forall\; t \in d. \tag{5.4}$$

We draw a random error, $e_{i,t,m} \forall t \in d$, for the m^{th} iteration of the bootstrap from $\mathcal{N}(0, \Sigma_d)$. For N customers in a single utility, the covariance matrix is:

$$\Sigma_d = \begin{bmatrix} \sigma^2_{1,d} & \rho\sigma_{1,d}\sigma_{2,d} & \cdots & \rho\sigma_{1,d}\sigma_{N,d} \\ \rho\sigma_{2,d}\sigma_{1,d} & \sigma^2_{2,d} & \cdots & \rho\sigma_{2,d}\sigma_{N,d} \\ \vdots & \vdots & \ddots & \vdots \\ \rho\sigma_{N,d}\sigma_{1,d} & \rho\sigma_{N,d}\sigma_{2,d} & \cdots & \sigma^2_{N,d} \end{bmatrix} \tag{5.5}$$

where ρ is the correlation of errors between customers. We assume the errors have correlation ρ across customers for each t in each utility since customers with geographical proximity are likely exposed to similar shocks.

We add the random error to our latent estimate and then censor it to obtain M censored load estimates $\upsilon_{i,t,m}$ for each customer i at each time $t \in d$:

$$\upsilon^*_{i,t,m} = \hat{y}^*_{i,t} + e_{i,t,m} \tag{5.6}$$

$$\upsilon_{i,t,m} = \begin{cases} 0 & \upsilon^*_{i,t,m} \leq 0 \\ \upsilon^*_{i,t,m} & 0 < \upsilon^*_{i,t,m} < \lambda_i \\ \lambda_i & \lambda_i \leq \upsilon^*_{i,t,m}. \end{cases} \tag{5.7}$$

We average across customers to obtain M average aggregated loads at each time, t:

$$\Upsilon_{t,m} = \frac{1}{N}\sum_{i=1}^{N} \upsilon_{i,t,m}. \tag{5.8}$$

We report the forecasted mean load at each time period, $\bar{\Upsilon}_t$, as the average across all bootstrap iterations:

$$\bar{\Upsilon}_t = \frac{1}{M}\sum_{m=1}^{M} \Upsilon_{t,m}. \tag{5.9}$$

We specify the α level CI by ordering the $\Upsilon_{t,m}$ and extracting the $\frac{1\pm\alpha}{2}$ observations as the CI.

We calculate ρ for each utility by doing a grid search over $0 \leq \rho \leq 1$. We perform this calculation separately for each utility since they would bid in separately. We calculate the percent of observations where the population average fits within the confidence intervals for the 50%, 90% and 95% confidence intervals for the within sample estimate. ρ is chosen to give the closest fit for the percentage of population values to the confidence interval.

5.4 Results

We fit the Tobit model described in section 5.3 to data from each data logger in our sample of customers. We used the models to forecast AC load each hour from August 15, 2010 to September 30, 2010. We use the following steps to produce hourly aggregate AC load forecasts each day during the simulation period.

1. Fit Tobit model to logger data collected up to day $d-2$.
2. Calculate an hourly forecast for each AC for day d.
3. Aggregate individual forecasts using the bootstrap method to get expected load and confidence intervals.
4. Repeat 1 - 3 for $d+1, d+2....$

Figures 5.2, 5.3 and 5.4 shows the median and upper and lower quartiles of the t-statistics for the $\hat{\beta}_{\chi,i}$ for all individual models. The customers are ordered by the magnitude of their t-statistics and the median, upper and lower quartile customers are extracted and plotted for each of the $\hat{\beta}_{\chi,i}$.

Aggregate forecasts were produced using the bootstrap method described in section 5.3. For each utility correlation coefficient ρ was estimated. Table 5.3 shows the correlation coefficients for each utility.

Table 5.3: Correlation coefficients for each utility.

	Utility		
	PEPCO	ACE	Delmarva
Correlation Coefficient ρ	0.12	0.27	0.15

Figure 5.5 shows the actual load, Tobit forecast and 50% confidence interval for the forecast for 5 days in August in the PEPCO utility.

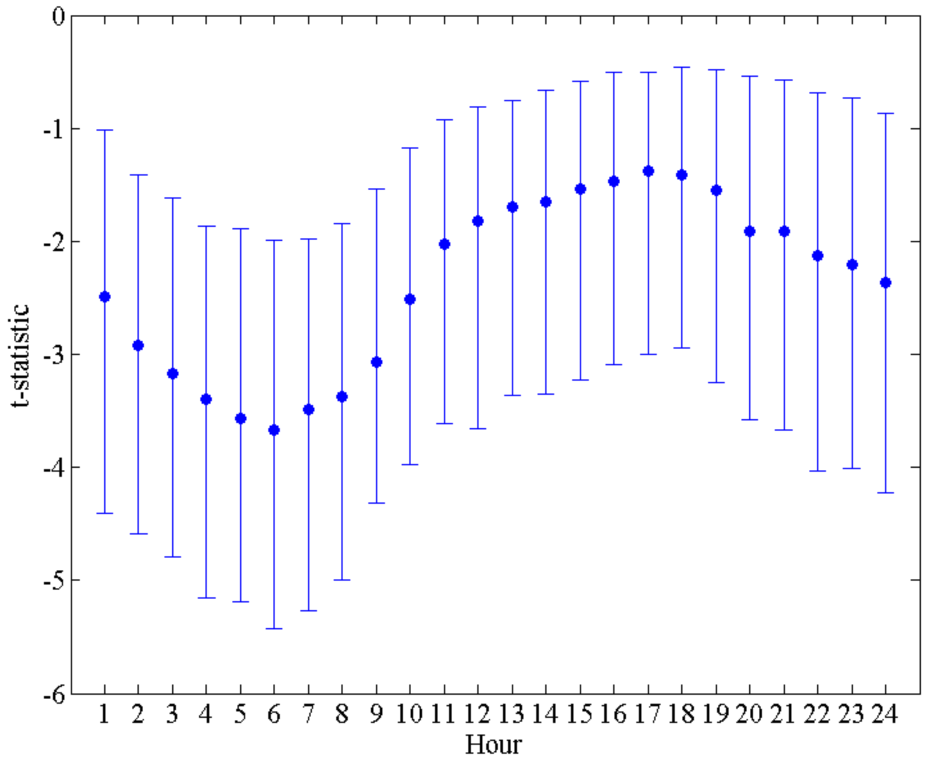

Figure 5.2: T-statistics for median, upper-quartile, lower-quartile customer for $\hat{\beta}_{D_h,i}$.

We compare the Tobit estimate to the default CBL used in the PJM RTO since PEPCO is in PJM territory. The default CBL in PJM is the average hourly load profile from the 4 highest load days of the previous 5 similar day types (weekdays, Saturdays, Sundays/holidays) (PJM, 2012). We did not do an intercept adjustment in the manner that PJM does for verification since this is a day-ahead forecast. Figure 5.6 compares the default CBL forecast to the Tobit forecast. Table 5.4 shows the mean squared error (MSE) for the default CBL and Tobit models. The Tobit model has an MSE that is an order of magnitude lower than the default CBL.

Since the Tobit model presented here uses hourly temperatures, it is important to see how well it performs over a range of temperatures. Figure 5.7 shows the

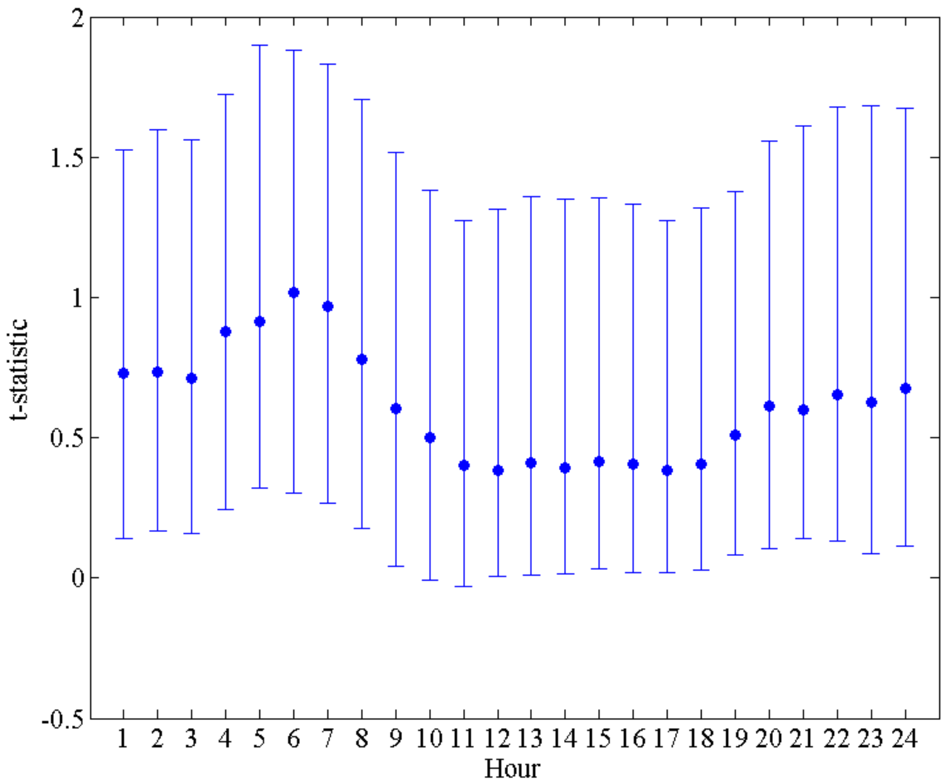

Figure 5.3: T-statistics for median, upper-quartile, lower-quartile customer for $\hat{\beta}_{TD_h,i}$.

forecast errors plotted against the ambient temperature. At high temperatures there is a tendency to over-forecast. One possible explanation for the bias at high temperatures is that vacations occur more frequently at the end of summer when we made our forecasts based on data collected earlier in the summer. A full summer of training data would likely improve the forecasts by allowing monthly indicators in the model.

5.5 Policy Implications and Discussion

Demand response is increasing in the US as a way to make the electric grid more reliable and provide services at a lower cost. Forecasting, measurement and verifi-

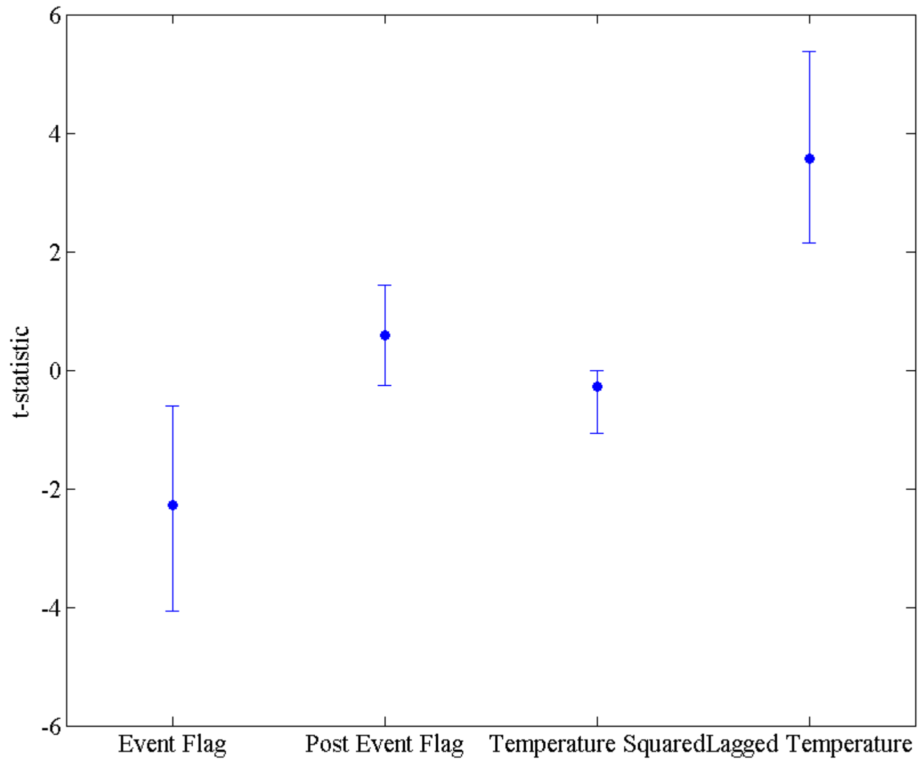

Figure 5.4: T-statistics for median, upper-quartile, lower-quartile customer for $\hat{\beta}_{E,i}$, $\hat{\beta}_{P,i}$, $\hat{\beta}_{T^2,i}$, $\hat{\beta}_{T1,i}$.

Table 5.4: Mean squared errors.

	Mean Squared Error	
	Tobit	default CBL
PEPCO	0.034	0.260
ACE	0.041	0.347
Delmarva	0.027	0.302

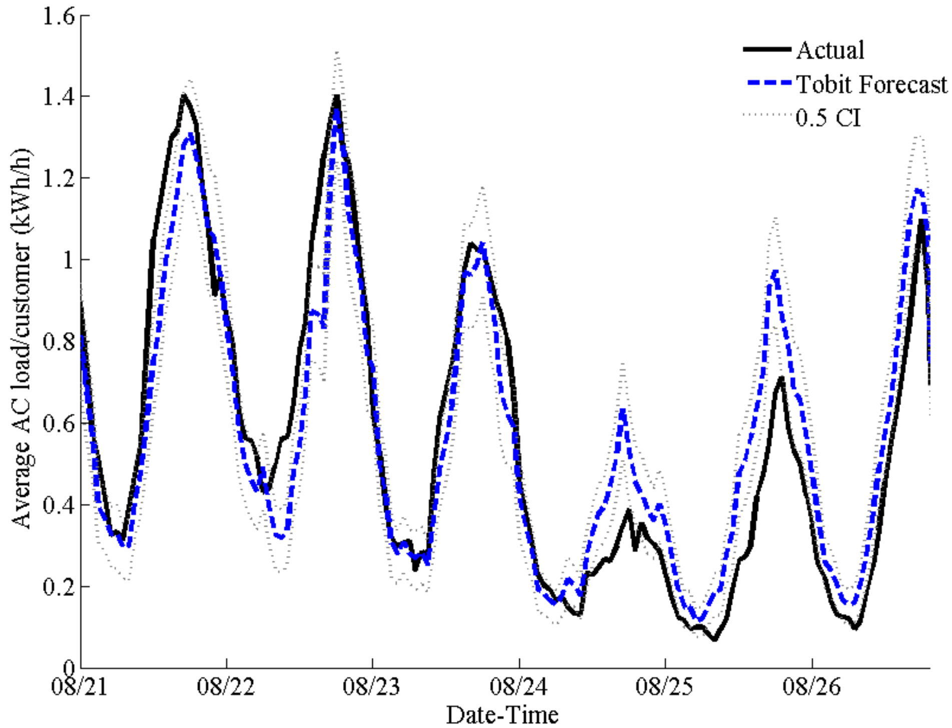

Figure 5.5: Average actual and forecasted AC usage for PEPCO with 50% confidence intervals.

cation of direct load control are becoming increasingly important, as penetration levels of demand response increase. Forecasting is important for system planning and measurement and verification are necessary to ensure that payments are fair. Forecasting, measurement and verification are difficult because we are measuring the quantity of power that was *not* used, and we must reconstruct a counterfactual situation.

We have developed a new, censored regression based model for forecasting the available direct load control resource. This forecast can be used for measurement and verification to determine AC load in the counternfactual where DLC is not applied. This method is more accurate than the typical moving averages used by most ISO's, and is simple, easy and cheap to implement. This method can

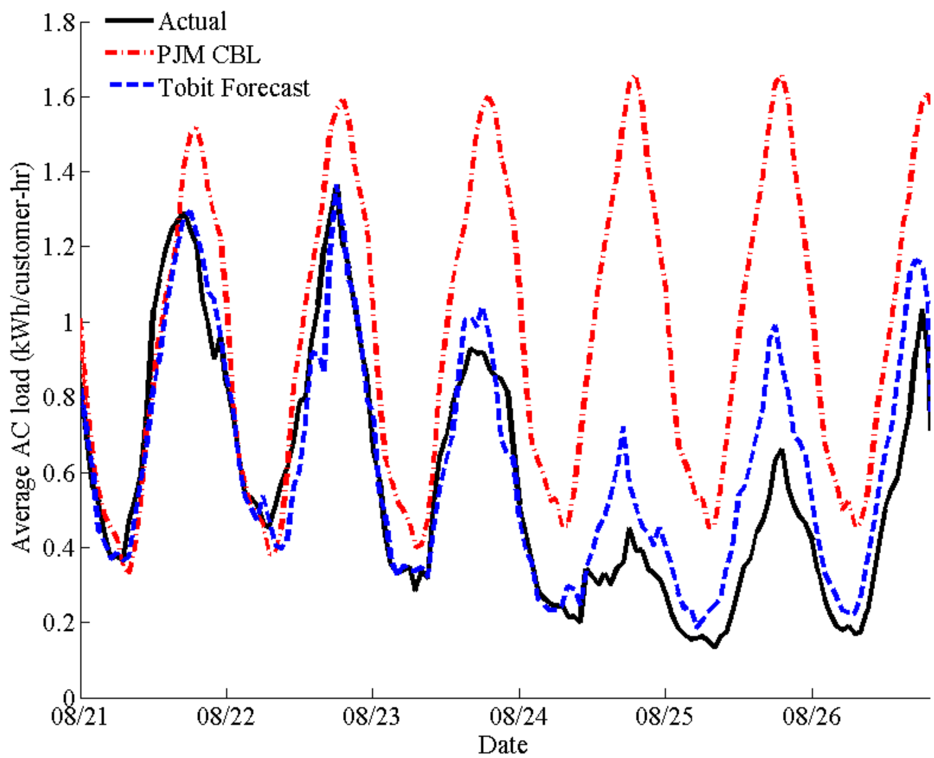

Figure 5.6: Comparison of Tobit forecast and default PJM CBL forecast for PEPCO data.

be further refined in future work, but introduces censored regression to load forecasting as an improvement on current forecasting methods.

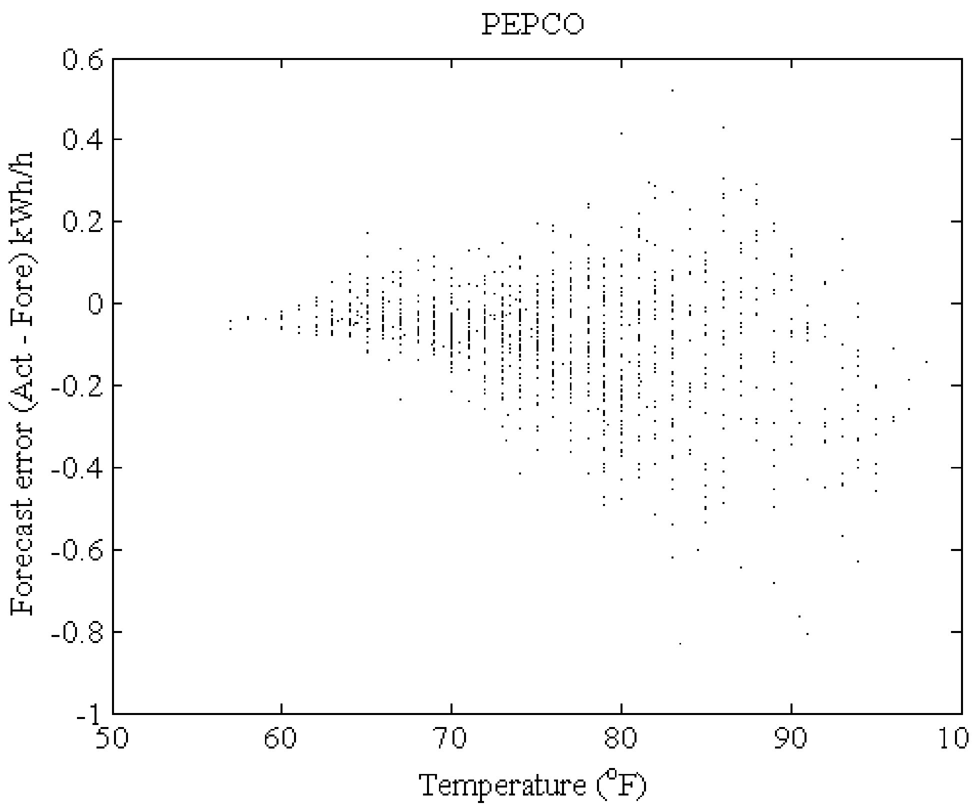

Figure 5.7: Forecast errors plotted against the ambient temperature from August 15, 2010 to September 30, 2010 in PEPCO.

Appendix A

ComEd Bills and Calculations for Chapter 3

This appendix shows the ComEd residential bill breakdown for FR and RTP (table A.2) with prices or prices ranges over 2007 and 2008 and major calculations used in this work including customer bills and bill difference. All information in this section comes from Commonwealth Edison Company (2006; 2007).

Table A.1: Indices used in calculations.

Symbol	Description	Set
i	Customer	
t	Time, hourly resolution	
r	Real-time price	
f	Flat rate price	
p	rate	$\{r, f\}$
c	Customer class	{single family, multi-family, single family space heat, multi-family space heat}
m	month	{Jan,... Dec$\in y$}
y	year	{2007, 2008}

Table A.2: ComEd residential bill breakdown.

Component	Charge name	Charge range: Flat rate	Charge range: RTP	Symbol
Electricity supply	Electricity supply charge	$4 - 8¢/kWh$	LMP $-25 - 50¢/kWh$	$ESC_{p,t,c}$
	Transmission service charge	$.2 - .8¢/kWh$	$0.2 - 0.8¢/kWh$	$TSC_{p,t,c}$
	Capacity obligation	0	$\$0.09 - 3/kWmt$	$CO_{p,m}$
	Purchased electricity adjustment	$-.1 - 2¢/kWh$	$-0.1 - 2¢/kWh$	$PEA_{p,t}$
	Miscellaneous procurement charge	0	0.3¢/kWh	$MPC_{p,t}$
Delivery service	Customer charge	$4.84/mt (MF), $6.67/mt (SF)		CC_c
	Metering charge	$2.21/mth		MC
	Distribution charge	about 2¢/kWh		DC_c
	Meter lease	0	$7.25/mt	ML_p
Taxes and other	Smart meter program	9¢/mth		SMP
	Environmental cost recovery	0.01¢/kWh		ECR_t
	Energy efficiency programs	0.147¢/kWh		EEP
	Franchise cost/state/municipal tax	varies - not included in calculation		

Note that the subscripts imply the variability of each variable. So $ESC_{p,t,c}$ varies with the rate, time and customer class, while MC is constant. Some components of the bills, which are fixed rates, or part of the flat rate do change over the course of the 2 year period in question, however these changes occur in intervals of one month or greater. The only part of the bill that changes hourly is the electricity supply charge under RTP, $ESC_{r,t,c}$.

Other variables $U_{i,t}$ is the actual usage of customer i at time t in kWh. D_i, Demand for customer i in kWh/h, coincident with PJM and ComEd peak demand. Calculated based on the average usage for each customer during the 5 hours of highest demand for all of PJM and the 5 hours of highest demand for the ComEd node for each year. There are only 19 hours since one hour overlapped for PJM and ComEd demand.

$$D_i = \frac{1}{19} \sum_{t \in A} U_{i,t} \tag{A.1}$$

Where, A = {7/9/2007:1600, 8/8/2007:1400, 8/8/2007:1500, 8/8/2007:1600, 8/8/2007:1700, 8/8/2007:1800, 8/7/2007:1600, 8/7/2007:1700, 8/7/2007:1800, 8/7/2007:1900, 6/9/2008:1500, 6/9/2008:1600, 6/9/2008:1700, 6/9/2008:1800, 7/16/2008:1600, 7/16/2008:1700, 7/16/2008:1800, 7/17/2008:1600, 7/17/2008:1700} (M/DD/YYYY:hhhh, hour ending, eastern prevailing time.).

Marginal price for customer $i \in c$, at time t, on rate p (\$/kWh):

$$M_{p,t,i} = ESC_{p,t,c} + TSC_{p,t,c} + PEA_{p,t} + MPC_{p,t} + DC_c + ECR_t + EEP. \tag{A.2}$$

Fixed monthly price for customer $i \in c$ on rate p for month m (\$/mth):

$$F_{p,m,i} = CO_{p,m} D_i + CC_c + MC + ML_p + SMP. \tag{A.3}$$

Monthly bill for customer i on rate p for month m (not including taxes) (\$/mth):

$$B_{p,m,i} = F_{p,m,i} + \sum_{t \in m} M_{p,t,i} U_{i,t}. \tag{A.4}$$

Annual bill for customer i on rate p for year m (not including taxes) (\$/yr):

$$B_{p,y,i} = \sum_{m \in y} B_{p,m,i}. \tag{A.5}$$

Annual bill difference for customer i during year y had he been on RTP:

$$\Delta_{i,y} = B_{f,y,i} - B_{r,y,i}. \tag{A.6}$$

Percentage difference in annual bill for customer i during year y had he been on RTP:

$$\delta_{i,y} = \frac{B_{f,y,i} - B_{r,y,i}}{B_{f,y,i}}. \tag{A.7}$$

Appendix B

Revenue Neutral Calculation for Chapter 3

The load weighted difference in FR and RTP prices are different for 2007 and 2008, so each year was made revenue neutral separately. The change to the FR marginal price (i.e. price per kWh) for 2007 to make it revenue neutral with respect to the RTP is -0.82¢/kWh with a 95% confidence interval of $[-0.88, -0.76]$. The change for 2008 is -0.34¢/kWh with a 95% confidence interval of $[-0.41, -0.27]$. Figure B.1 shows the distribution for each year separately and both years together along with a 95% confidence interval for both years. It is difficult to make out the plots individually since they are statistically indistinguishable at the 95% confidence interval. For ease of presentation, results for 2007 and 2008 are shown together throughout the chapter. The implications do not change by separating the years.

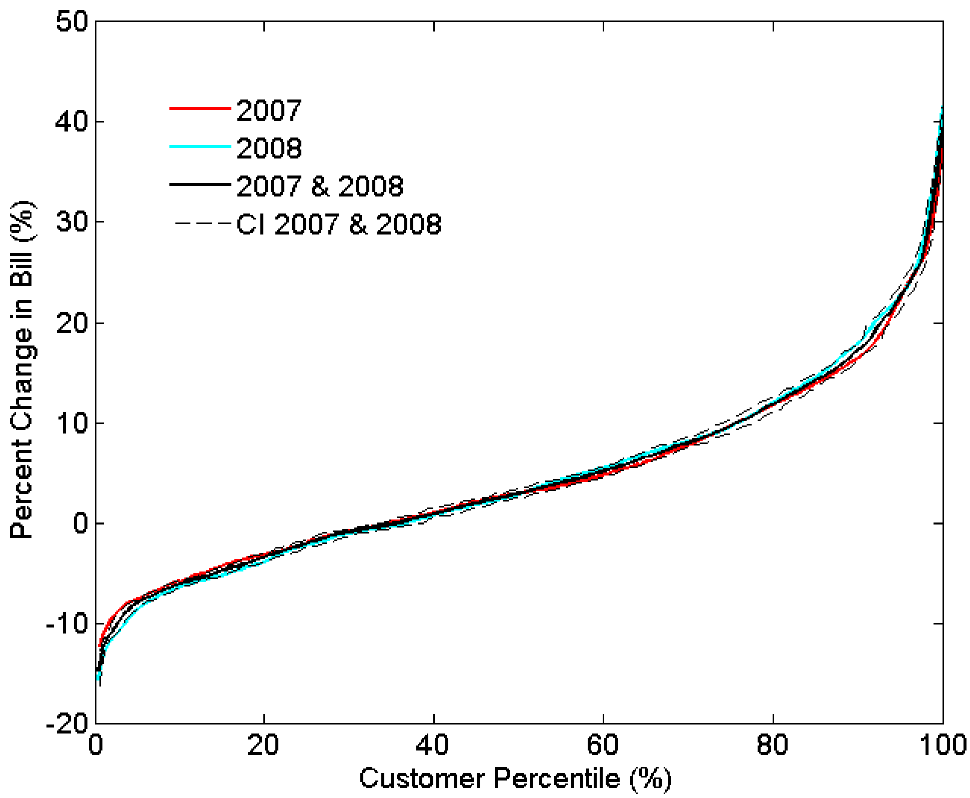

Figure B.1: The distribution for changes in bill for 2007, 2008 and both years together and a 95% confidence interval for both years together.

Appendix C

Bootstrap Technique for Chapter 3

Since the sampling rate was different for each of the 4 customer classes, bootstrapping was used to get statistics and distributions with confidence intervals for the entire population. No inferences outside the range of the data are made.

The total sample size is N. For each iteration of the bootstrap, the number of samples drawn from each customer class, η_c, is drawn from a $multinomial(n = N, p = [\pi_1, \pi_2, \pi_3, \pi_4])$ where π_c is the proportion of customer class c in the population. η_c observations are then randomly drawn with replacement from customer class c, for a total of N observations for each iteration of the bootstrap.

A statistic, θ_i was then computed for each iteration, i, of the bootstrap. The mean $\bar{\theta} = \frac{1}{N}\sum_{i=1}^{N}\theta_i$ is reported as the statistic. 95% confidence intervals are reported by ordering the statistics across iterations and extracting the 2.5th and 97.5th observations of the θ_i.

Distributions were computed by binning the data into approximately 200 bins (this value was slightly varied depending on N so that there would be a discrete number of observations in each bin) for each iterations. The mean value across all iterations is reported for the distribution. Confidence intervals are reported using the same method as the statistics. The distribution was not sensitive to change in bin number in the range of $100 - 500$ bins.

1000 iterations of the bootstrap were done. No improvement in accuracy was observed for more than 1000 iterations.

Appendix D

Data Cleanup for Chapter 3

The raw data consisted of 37.8 million hourly electricity usage observations from 3082 customers. The data were cleaned to remove outlying or otherwise suspect data. When suspect data was removed, 35.5 million observations and 2962 customers remained. The following criteria were used to remove data:

1. Any usage observations of 0 were removed. The remaining data for that customer was left in.

2. Many customers had extreme values for a number of consecutive observations starting with their first observation. These data were deleted, however the remaining data for that customer was left in.

3. If a customer had any extreme observations after beginning consecutive observations were removed, all the data for that customer were removed.

4. ComEd filled in missing data for customers by alternating three values over the missing observations representing previous averages over different hours of the day for that customer. If more than 10% of a customerâĂŹs data consisted of these average values, the entire customer was removed from the data.

Outliers are defined as any hourly observation exceeding these thresholds: 25 kWh/h for SF; 12 kWh/h for MF; 75 kWh/h for SFH; and 36 kWh/h for MFH.

Since electricity usage and price both have seasonal variations, it was important to analyze bill differences over an entire year for a customer. Therefore, of the customers who remained after suspect data was removed, only 1260 customers (consisting of 15.2 million total observations) who had at least one complete year of data (either complete 2007, complete 2008, or both) were used for the analysis.

To ensure that removing customers who did not have a complete year of data did not bias the dataset (for example, frequent movers would be removed disproportionally and may have different usage patterns) we performed an independent sample t-test with pooled variance between the mean usages for customers who had complete years of data and those who didn't (with suspect data removed). We split this by customer class and month. We were not able to reject the null hypothesis that the means were the same at the 95% confidence level for any customer class and month.

Appendix E

LMP Calculation for Chapter 3

We re-calculate LMPs under elastic demand using the existing supply curve for the ComEd node of PJM during 2007 and 2008. We initially tried a parametric regression using all the data from the two year period. This gave us results that were sufficient for looking at price averages and statistics over certain periods of time, however these results were insufficient for comparing to single hours. For example, the model told us that for some hours, if demand dropped, price would increase. The model was giving correct information for a similar situation on average, however we reject that price would increase as demand drops for the same exact hour. Instead we use a non-parametric method that essentially constructs a supply curve for small changes in demand for each hour individually. The algorithm follows:

(D_t, P_t) = actual ComEd Demand D and System LMP P at time t,

$A = \{(D_i, P_i)...\}$ = set of (D_i, P_i) for $i = t - xtot + x (x = 7)$,

D_0 = new, unobserved ComEd Demand based on customer elasticity,

P_0 =unobserved price corresponding to D_0 - this is what we are trying to calculate.

1. Select 2 observations from A and assign to (D_1, P_1) and (D_2, P_2) such that:

    (a) $D_i \leq D_0$ and $min(D_i - D_0)$ then assign to D_1 and corresponding P_i to P_1. If no $Di \leq D_0$ then $P_0 = min\{Pi\}$.

    (b) Assign D_i to D_1 only if $P_i \leq P_t$. If $P_i > P_t$ then remove (D_i, P_i) from $A$and go back to (a).

    (c) Assign (D_i, P_i) to (D_2, P_2) such that $min(D_i - D_0)$ and $(D_i - D_0) > 0$.

    (d) Must have $P_2 > P_1$. If not then remove (D_2, P_2) from A and go back to (c).

    (e) If no $P_i > P_1$ and $D_i > D_0 > D_1$ then $P_0 = min\{P_i\}$.

2. If P_0 has not yet been assigned and $D_2 > D_0 > D_1$ and $P_2 > P_1$ then assign P_0 using linear interpolation as follows: $P_0 = P_1 + (D_0 - D_1)\frac{P_2 - P_1}{D_2 - D_1}$.

Appendix F

Elasticity Analysis for Chapter 3

The following was done to calculate statistics for bill differences with an elasticity.

1. N customers are randomly selected from the sample (total sample size = N) with replacement so that the sample is representative of the population. These customers now constitute the set A.

2. The elasticity is applied to all customers in A during hours when the real time price exceeds a certain threshold and the temperature exceeds a certain threshold. It is also applied to customers with electric space heating during hours when the price exceeds a certain threshold and the temperature is below a different threshold.

3. New system wide demand is calculated by summing the change in demand across customers, scaling this up from the sample size to the population size, and subtracting it from the actual total demand during that hour.

4. A new price is calculated for each hour based on the new system wide demand, using linear interpolation (see below for the algorithm).

5. New capacity obligations are calculated for each customer by averaging their new, elastic usage during the 10 peak hours of the year (customers pay (capacity obligation in kW)$\times$(capacity price in \$/kW-mth) each month).

6. Flat rate bills are calculated based on non-elastic usage and RTP prices are calculated based on elastic usage, new capacity obligation and the new price for each customer in A.

7. The difference between the FR and RTP is then calculated and summed for the total savings.

8. (1) - (7) is repeated 1000 times. Statistics on the sum calculated in (7) are reported by taking the mean as the point estimate and the 2.5th percentile and 97.5th percentile of the ordered sums as the 95% probability interval. A distribution of bill differences is made by averaging across savings for each observation (i.e. ordering customers by savings, then averaging the customer with the most savings for every bootstrap iteration, the customer with the 2nd to most savings across every iteration, etc.).

Appendix G

Selected SAS Code from Chapter 4

```
%LET lib = db8;  /*Permanent Library*/
%LET gp = 4 - Single Family RTP;  /* group that &accnt belongs to*/
%LET out_file = reg4d_out.html;

%LET Qdif = 168; /* number of periods to differnce logQ by*/

%LET TempShift = 60; /*Temp threshold where create
   2 different variables -- above = heating deg
   below = cooling deg*/
%LET TempThreshPrice = 90; /*Temperature threshold where create
 2 different price variables*/

%MACRO hr_mac(type);
%DO i =0 %TO 23;
 &type&i
```

```
%END;

%MEND hr_mac;


/*Macro for PROC AUTOREG with the account as the argument*/

%MACRO AUTOREGaccnt(accnt_no);


PROC SORT

DATA = db8_gp4.gp4_2005_&accnt_no

OUT = work.data_set;

BY date_time;

RUN;



PROC MEANS

DATA = work.data_set

NOPRINT

MEAN

;

VAR  no_agg_use4;

OUTPUT

OUT = work.mean_use

mean = avg_use

;

RUN;



/* Creates additional variable for regression
```

```
   including lagged variables, differenc variables
   shift for temp variable etc*/

DATA work.data_set3;
SET work.data_set;
date = DATEPART(date_time);
Q = no_agg_use4;
logQ = log(Q);
diflogQ = dif&Qdif(logQ);
PriceC = price*100; /*price in cents*/
Thi = temp - &TempShift; /*Temps above 60F, shifted down by 60 deg, else
   0*/
Tlo = temp - &TempShift;/*Temps below 60F, shifted down by 60 deg, else
  0*/
IF Thi < 0 THEN Thi = 0;
ELSE IF Tlo > 0 THEN Tlo = 0;
thi2 = Thi*Thi;
ThiI = 0; /*Indicator function for when temp is above &TempThreshPrice*/
TloI = 0; /*Indicator function for when temp is below &TempThreshPrice*/
IF temp GE &TempThreshPrice THEN ThiI = 1;
ELSE IF temp < &TempThreshPrice THEN TloI =1;
PTHiI = priceC*ThiI;
PTLoI = priceC*TloI;
P2ThiI = priceC*priceC*ThiI;

/* Arrays for dummy variables for hour of day when temp is below/above
   &tempshift*/
```

```
ARRAY hr_lo_array {0:23} hr_lo0 - hr_lo23;
ARRAY hr_hi_array {0:23} hr_hi0 - hr_hi23;
DO i = 0 to 23;
hr_lo_array{i} = 0;
hr_hi_array{i} = 0;
END;
hr_lo_array{hour(date_time)} = abs(sign(Tlo));
hr_hi_array{hour(date_time)} = abs(sign(Thi));

LABEL Q = "Household consumption group &gp accnt &accnt_no, kWh/h"
logQ = "log of Q, Q = Household consumption group &gp accnt
&accnt_no, kWh/h"
Thi = "Temps above &TempShift F, shifted by &TempShift, else 0"
Tlo = "Temps below &TempShift F, shifted by &TempShift, else 0"
Thi2 = "Thi^2"
ThiI = "Indicator function for when temp is above &tempshift"
TloI = "Indicator function for when temp is below &tempshift"
PTHiI = "priceC*ThiI"
PTLoI = "priceC*TloI"
P2ThiI = "priceC^2*ThiI"
PriceC = "Real time price, cents/kWh"
;
FORMAT date date9.;
RUN;

ODS LISTING CLOSE;
ODS OUTPUT ParameterEstimates = work.parms;
```

```
PROC AUTOREG

DATA = work.data_set3

PLOTS = none

;

MODEL diflogQ =  %hr_mac(hr_lo) %hr_mac(hr_hi) PTloI PThiI tlo

thi thi2

/NOINT

METHOD = ml

NLAG = (1 24 168)

;

RUN; QUIT;

ODS OUTPUT CLOSE;

ODS LISTING;


DATA _null_;

SET work.parms;

IF VARIABLE = 'PTHiI'

THEN DO;

CALL SYMPUT('VPTHiIB',estimate);

CALL SYMPUT('VPTHiIT',tValue);

CALL SYMPUT ('VPTHiIP',pValue);

END;

IF VARIABLE = 'PTLoI'

THEN DO;

CALL SYMPUT('VPTLoIB',estimate);

CALL SYMPUT('VPTLoIT', tValue);

CALL SYMPUT ('VPTLoIP',pValue);
```

```
END;

RUN;

DATA _null_;
SET work.mean_use;
CALL SYMPUT('avg_use', avg_use);
RUN;

DATA work.parms2;
account = symget('accnt_no')*1;
PThiI_beta = symget('VPTHiIB')*1;
PThiI_t= symget('VPTHiIT')*1;
PTloI_beta= symget('VPTLoIB')*1;
PTloI_t= symget('VPTLoIT')*1;
PTloI_P= symget('VPTLoIP')*1;
PThiI_P= symget('VPTHiIP')*1;
AVG_HR_USE = symget('avg_use')*1;
RUN;

PROC APPEND
BASE = db8.gp4_price_vars
DATA = work.parms2
FORCE;
RUN;

%MEND AUTOREGaccnt;
```

```
/* Data Set for \beta and t-stats for price params*/
DATA db8.gp4_price_vars;
account = .;
PThiI_beta = .;
PThiI_t = .;
PTloI_beta = .;
PTloI_t = .;
PTloI_P = .;
PThiI_P = .;
AVG_HR_USE = .;
LABEL account = "Account Number"
PThiI_beta = "Parameter estimate for PThiI"
PThiI_t =  "T-stat for parameter estimate for PThiI"
PTloI_beta = "Parameter estimate for PTloI"
PTloI_t = "T-stat for parameter estimate for PTloI"
PTloI_P = "P-value for parameter estimate for PTloI"
PThiI_P = "P-value for parameter estimate for PThiI"
AVG_HR_USE = "Average hourly electricity use (kWh/h)"
;
RUN;

DATA _NULL_;
SET db8.gp4_accounts_full_2005;
CALL SYMPUT('accnt_no'||put(_n_,8. -L), put(account, 10. -L));
RUN;
```

```
/* get # of good accounts*/
%LET dsid = %SYSFUNC(OPEN(db8.gp4_accounts_full_2005));
%LET tot_accnts = %SYSFUNC(ATTRN(&dsid, nlobs));
%LET RC = %SYSFUNC(CLOSE(&DSID));

%MACRO runAllAccnts;
%DO j = 1 %TO &tot_accnts;
%AUTOREGaccnt(&&accnt_no&j)
%END;
%MEND runALLAccnts;

%runAllAccnts;
```

G.1 Data Cleaning Protocol

We removed ACs with poor data quality from the analysis. We describe here what metrics we used to determine the data quality.

Six loggers had too few observations (fewer than 9 days; the remaining loggers all had mroe than 52 days) and were removed. The data from 2 loggers were logged at the wrong frequency (1 minute and 5 minute instead of three minute) and were removed. Some of the loggers showed that the AC was rarely used (less than 3 hours during the entire summer). Obviously, a model will predict zero load for a household that never uses the AC. Data from these loggers were not analyzed since they provided no information for our forecasts. Several ACs had 20A loggers even though the AC capacity was greater than 20A. If a logger logged data at 20A more than 10% of the time, we assume that it required a higher amperage logger, and discard the data. There were also several loggers that became stuck on a particular value. We removed any logger from the dataset that switched state (from off to on or vice versa) in fewer than 2% of its observations. Finally, we removed loggers that had unrealistically low readings (all observations below 3 amps). A summary of the number of logger data discarded is in table G.1.

Table G.1: Number of loggers discarded from the dataset.

Data Problem	Number of loggers
Length of time less than 9 days	6
Incorrect time intervals	2
AC nearly always off	10
Logger maxed out	11
Stuck logger	13
Values unrealistically low	27
Total discarded	69

G.2 Tobit Derivations

We derive the likelihood function and heteroscedasticity and autocorrelation consistent (HAC) variances for the Tobit model in this section. Our derivation for the HAC variance is based on Bernard and Busse (2003).

This is a general derivation for a doubly-censored Tobit model. Lower and upper bounds for censoring are represented here as a and b. For the model presented in this thesis, $a = 0$ and $b = \lambda$. To simplify the notation, we drop i, the index for AC from the derivations, since the maximum likelihood estimate for each AC is done separately.

The latent variable is:

$$y_t^* = \boldsymbol{X_t'\beta} + \epsilon_t. \tag{G.1}$$

The censored variable is:

$$y_t = \begin{cases} a & y_{i,t}^* \leq a \\ y_{i,t}^* & a < y_{i,t}^* < b \\ b & b \leq y_{i,t}^*. \end{cases} \tag{G.2}$$

We define indicator variables:

$$I_t(a) = \begin{cases} 1 & y_t^* \leq a \\ 0 & a < y_t^* \end{cases} \tag{G.3}$$

$$I_t(ab) = \begin{cases} 1 & a < y_t^* < b \\ 0 & y_t^* \leq a \bigcup b \leq y_t^* \end{cases} \tag{G.4}$$

$$I_t(b) = \begin{cases} 1 & b \leq y_t^* \\ 0 & y_t^* < b. \end{cases} \tag{G.5}$$

We assume the latent variable, y_t^* has distribution $\mathcal{N}(\mu, \sigma^2)$. The entire probability density of the lower censored region is applied at a, and the same for the upper censored region at b. The probability density function for the censored variable is:

$$
\begin{aligned}
f(y_t) &= \begin{cases} \Phi\left(\frac{a-\mu}{\sigma}\right) & y_t^* \le a \\ \frac{1}{\sigma}\phi\left(\frac{y_t-\mu}{\sigma}\right) & a < y_t^* < b \\ 1-\Phi\left(\frac{b-\mu}{\sigma}\right) & b \le y_t^* \end{cases} \\
&= \begin{cases} \Phi\left(\frac{a-\mu}{\sigma}\right) & y_t^* \le a \\ \frac{1}{\sigma}\phi\left(\frac{y_t-\mu}{\sigma}\right) & a < y_t^* < b \\ \Phi\left(\frac{\mu-b}{\sigma}\right) & b \le y_t^* \end{cases}
\end{aligned} \tag{G.6}
$$

where $\Phi(z)$ is the cumulative density function (CDF) and $\Phi(z)$ is the probability density function (PDF) for the standard normal distribution $\mathcal{N}(0, 1)$.

The likelihood function $\mathcal{L}(\boldsymbol{X_t}, \theta)$ and log-likelihood function $\ell(\boldsymbol{X_t}, \theta)$ are expressed in terms of the vector of parameters $\boldsymbol{\theta} = [\boldsymbol{\beta}' \ \sigma]'$ and τ, the length of the time-series:

$$
\mathcal{L}(\boldsymbol{X_t}, \boldsymbol{\theta}) = \prod_{t=1}^{\tau} f(y_t) \tag{G.7}
$$

$$
\begin{aligned}
\ell\left(\boldsymbol{X_t}, \boldsymbol{\theta}\right) &= ln(\mathcal{L}) \\
&= \sum_{t=1}^{\tau} ln(f(y_t)) \\
&= \sum_{t=1}^{\tau} \Bigg[I_t(a) ln\left(\Phi\left(\frac{a-\mu}{\sigma}\right)\right) + I_t(ab) ln\left(\frac{1}{\sigma}\phi\left(\frac{y_t-\mu}{\sigma}\right)\right) \\
&\qquad + I_t(b) ln\left(\Phi\left(\frac{\mu-b}{\sigma}\right)\right)\Bigg]
\end{aligned} \tag{G.8}
$$

where

$$\mu = \boldsymbol{X_t'\beta} \tag{G.9}$$

$$\frac{1}{\sigma}\phi\left(\frac{y_t-\mu}{\sigma}\right) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{-(y_t-\mu)^2/2\sigma^2}. \tag{G.10}$$

We insert (G.9) and (G.10) into (G.8) to obtain:

$$\begin{aligned} \ell(\boldsymbol{X_t},\boldsymbol{\theta}) = \sum_{t=1}^{\tau}\Bigg[& I_t(a)ln\left(\Phi\left(\frac{a-\boldsymbol{X_t'\beta}}{\sigma}\right)\right) - I_t(ab)\frac{1}{2}ln\left(2\pi\sigma^2\right) \\ & - I_t(ab)\frac{(y_t-\boldsymbol{X_t'\beta})^2}{2\sigma^2} + I_t(b)ln\left(\Phi\left(\frac{\boldsymbol{X_t'\beta}-b}{\sigma}\right)\right)\Bigg]. \end{aligned} \tag{G.11}$$

The gradient of likelihood function is:

$$\nabla\ell(\boldsymbol{X_t},\theta) = \begin{bmatrix} \frac{\partial\ell}{\partial\beta} \\ \frac{\partial\ell}{\partial\sigma} \end{bmatrix} \tag{G.12}$$

where the gradient with respect to β is:

$$\begin{aligned} \frac{\partial\ell}{\partial\beta} = \sum_{t=1}^{\tau}\Bigg[& I_t(a)\frac{\phi\left(\frac{a-\boldsymbol{X_t'}\beta}{\sigma}\right)}{\Phi\left(\frac{a-\boldsymbol{X_t'}\beta}{\sigma}\right)}\left(-\frac{\boldsymbol{X_t}}{\sigma}\right) + I_t(ab)\frac{(y_t-\boldsymbol{X_t'\beta})\boldsymbol{X_t}}{\sigma^2} \\ & + I_t(b)\frac{\phi\left(\frac{\boldsymbol{X_t'}\beta-b}{\sigma}\right)}{\Phi\left(\frac{\boldsymbol{X_t'}\beta-b}{\sigma}\right)}\left(\frac{\boldsymbol{X_t}}{\sigma}\right)\Bigg] \end{aligned} \tag{G.13}$$

and the gradient with respect to σ is:

$$\begin{aligned} \frac{\partial\ell}{\partial\sigma} = \sum_{t=1}^{\tau}\Bigg[& I_t(a)\frac{\phi\left(\frac{a-\boldsymbol{X_t'}\beta}{\sigma}\right)}{\Phi\left(\frac{a-\boldsymbol{X_t'}\beta}{\sigma}\right)}\left(\frac{\boldsymbol{X_t'\beta}-a}{\sigma^2}\right) - I_t(ab)\frac{1}{\sigma} \\ & + I_t(ab)\frac{(y_t-\boldsymbol{X_t'\beta})^2}{\sigma^3} + I_t(b)\frac{\phi\left(\frac{\boldsymbol{X_t'}\beta-b}{\sigma}\right)}{\Phi\left(\frac{\boldsymbol{X_t'}\beta-b}{\sigma}\right)}\left(\frac{b-\boldsymbol{X_t'\beta}}{\sigma^2}\right)\Bigg]. \end{aligned} \tag{G.14}$$

A term in the gradient is in indeterminate form for $z < -38$:

$$\lim_{z \to -\infty} \frac{\phi(z)}{\Phi(z)} = \frac{0}{0} \tag{G.15}$$

so we apply L'Hôpital's rule:

$$\begin{aligned} \lim_{z \to -\infty} \frac{\phi(z)}{\Phi(z)} &= \lim_{z \to -\infty} \frac{d\phi(z)/dz}{d\Phi(z)/dz} \\ &= \lim_{z \to -\infty} \frac{-z\phi(z)}{\phi(z)} \\ &= -z. \end{aligned} \tag{G.16}$$

The auto-covariance is

$$\gamma(\delta) = \frac{1}{\tau - \delta} \sum_{t=1}^{\tau-\delta} \nabla \ell(\boldsymbol{X_t}, \theta) \nabla \ell(\boldsymbol{X_{t+\delta}}, \theta)'. \tag{G.17}$$

The Newey-West weights are expressed as:

$$\omega(\delta) = 1 - \frac{\delta}{\Delta + 1} \tag{G.18}$$

where $\Delta \leq \sqrt{\tau}$, we use $\Delta = \tau^{0.4}$. The variance of likelihood estimate with the HAC correction is expressed in terms of the auto-covariance and Newey-West weights:

$$Var \nabla \ell = \omega(0)\hat{\gamma}(0) + \sum_{\delta=1}^{\Delta} \omega(\delta) \left(\hat{\gamma}(\delta) + \hat{\gamma}(-\delta)' \right). \tag{G.19}$$

The variance with HAC correction are expressed in terms of (G.19) and the Hessian H:

$$Var(\theta) = (-H)^{-1} Var \nabla \ell (-H/\tau)^{-1}. \tag{G.20}$$

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