EFFICIENT PRICING IN ELECTRICITY MARKETS:

WHO IS ON REAL-TIME PRICING

An Honors Fellows Thesis

by

MICHELLE FONTANA

Submitted to the Honors Programs Office
Texas A&M University
in partial fulfillment of the requirements for the designation as

HONORS UNDERGRADUATE RESEARCH FELLOW

April 2011

Major: Economics

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ABSTRACT

Efficient Pricing in Electricity Markets: Who Is on Real-Time Pricing? (April 2011)

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When prices are set properly, they serve as important signals to guide customers to consume the efficient quantity of a good. However, in electricity markets many consumers do not pay prices that reflect the scarcity of power. The true social cost of power varies throughout a typical day; power is usually low cost during off-peak periods in the night but it is high cost during a hot July afternoon. Economists have argued for several decades that consumers should pay a price that varies with the true social cost of power. However, the vast majority of consumers pay a fixed price whether they use power at midnight or noon. This can create a host of economic inefficiencies. Fortunately, this is beginning to change. In many states, including Texas, large commercial and industrial users of electricity pay prices that reflect the social cost of power at the time of consumption. This pricing mechanism is called “real-time pricing” (RTP) in electricity markets. I have access to a unique, new dataset of virtually all 8000 commercial and industrial users in Texas that includes information on both whether they pay real-time prices and their hourly consumption for one year. First, I econometrically estimate the types of commercial and industrial firms that are likely to “sign up” for time-varying prices. Second, I test whether the customers on real-time prices reduce demand substantially in response to higher prices. I find that customers with greater total hourly consumption are more likely to be on real-time pricing. Customers with more “peaky” load profiles are less likely to be on real-time pricing. Customers in south and west Texas have a greater probability of being on RTP than customers in Houston. I also study whether customers on RTP decrease consumption on hot summer days when electricity is scare. These results have important implications for the design of both deregulated electricity markets and policies that seek to increase the amount of electricity generated with renewable sources of energy.

ACKNOWLEDGMENTS

I first owe a great amount of thanks to my advisor, Steve Puller of the Texas A&M Economics Department for his guidance through the research process and sharing of the unique data set from ERCOT. I also would like to thank Cesar Cancho for all of his help with the data set and STATA software. I am very grateful to my parents, Joseph and Marianne Fontana, for their constant support of my academic endeavors.

This research is based on a broad research project of studying real-time pricing by Steve Puller and Cesar Cancho.

NOMENCLATURE

ERCOT	Electric Reliability Council of Texas
RPS	Renewable Portfolio Standards
RTP	Real-Time Pricing

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

INTRODUCTION

Economists tout the benefits of prices. When they are set properly, prices serve as important signals to guide customers to consume the efficient quantity of a good. However, in electricity markets many consumers do not pay prices that reflect the scarcity of power. Electricity is unique in that it cannot be stored for future use. Supply must equal demand at every second to ensure an efficiently operating grid or network. The true cost of power is the wholesale price of electricity generation which varies throughout a typical day; power is usually low cost during off-peak periods in the night but is high cost during a hot July afternoon. During periods of peak demand, the true social cost (and wholesale price) of power is very high, but consumers still face the same flat-rate price. For example, during the recent January 2011 ice storm that hit much of Texas, consumers did not face strong signals to conserve power because their price remained constant. The grid operator could not meet demand and inefficiently selected particular areas to receive electricity and others to not as a result. This outcome of rolling blackouts fails to allow some customers with high willingness to pay to get power and gives power to some who value it much less.

The great amount of variation in the wholesale price of electricity is rather surprising. Figure 1 displays the variation in wholesale price and demand during a typical summer

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This thesis follows the style of *American Economic Review*.

day in Texas. The black dotted line plotted on the right axis shows unsurprisingly that people consume more in the afternoon than the middle of the night. The yellow line plotted on the left axis shows the variation in the wholesale price of electricity. Surprisingly, wholesale prices on a hot afternoon can be four times higher than prices in the middle of the night. In Figure 1, the wholesale price changes from about $ 25 in the middle of the night to $ 140 in the afternoon within one day (or $ .25 and $1.4 in retail price). Thus, retail prices that truly reflect scarcity of power should vary dramatically over the course of a day if prices are to send proper signals.

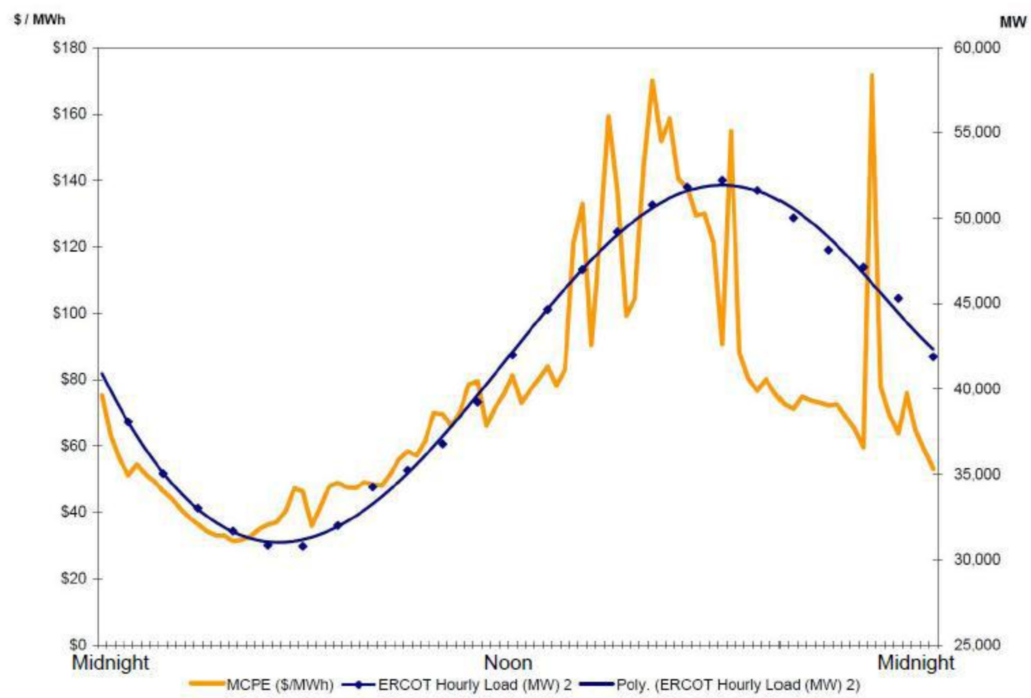

Figure 1. Stylized Picture of Load Profile and Wholesale Price Over a Day

Source: Adapted from Puller 2010: 3.

The solution to the inefficiency of flat-rate pricing and rolling blackouts is real-time pricing (RTP) or "retail pricing that changes hourly to reflect changing supply/demand balance" (Borenstein, 2005). RTP more closely follows the volatility of the wholesale electricity market, allowing retailers to signal cost shifts to customers. Other benefits are also well noted by other economists. Holland and Mansur show that RTP adoption provides efficiency gains in both the short and long run (Holland and Mansur, 2005). According to Borenstein and Holland, flat rates in competitive electricity markets fail to reach the first or second optimal result; taxes and subsidies in competitive electricity markets create additional inefficiencies that fail to solve the inefficiency of non-time varying prices (Borenstein and Holland, 2004). Holland and Mansur also show that RTP reduces the variance of demand within days and across days (Holland and Mansur, 2004). They show that consumers benefit as RTP adoption increases, since all rates, including RTP and flat rates decrease (Holland and Mansur, 2005).

Producers benefit from lower peak demand and less “low-capital/high-variable-cost peaker generation” or expensive generators used only in high demand situations (Borenstein, 2005). Finally, RTP facilitates the increased development of renewable sources of energy. A major problem with renewable energy sources is “intermittency”--wind and solar power cannot always provide reliable power because wind speed and sunshine cannot be perfectly predicted. Usually, if renewable generators fail to provide power for several hours, then high cost “quick start” generators are turned on so that supply meets demand. A lower cost alternative to expensive back-up generators is to to reduce demand via RTP.

In Texas, all electricity customers, including commercial and industrial customers, can choose to purchase electricity from any retail electric provider. For commercial and industrial customers, the structure of the rates is bilaterally negotiated between the customer and the retail provider. This stands in marked contrast to some states in which tariffs are imposed by a regulator. Thus, in Texas, the commercial and industrial customers have great flexibility to design rates that vary with time of use and include many possible means to hedge against bill volatility. I study the extent to which these negotiated rates include RTP.

The theory behind the choice behavior of both electricity customers and retail providers sheds light on their motivations for choosing RTP contracts. Electricity customers have the potential to reduce their electricity bills with RTP. If most of a customer's electricity consumption is during non-peak periods, that customer would most likely reduce their electricity bill because of the difference between the low non-peak price they face after RTP adoption and higher constant flat-rate price they paid before RTP adoption. Customers that are environmentally conscious or would like to increase the energy efficiency of their business could reduce their consumption through RTP adoption. The volatility of RTP and the large fixed costs associated with the technology needed to measure electricity usage in small increments of time suggests that larger firms are more apt to adopt RTP. Smaller customers may not be able to bear the costs associated with the volatility in RTP, particularly during peak periods. And larger customers may be more able to adopt RTP due to their ability to better handle large fixed costs. More generally, some customers may be risk adverse to volatile bills and thus be willing to pay a premium for flat-rate pricing.

System operators would prefer that customers sign RTP contracts for a variety of reasons. First, RTP reduces peak demand and thus reduces the amount of stress that is put on the electricity grid. This also reduces the potential for rolling blackouts. Second, retail providers can pass the costs associated with the peak periods onto their customers. RTP reduces the need for expensive back-up generators during periods of extremely high demand. Finally, retailers can benefit from having customers under RTP contracts because these contracts shift some of the price risk onto customers. RTP allows the retail price to more closely follow the wholesale spot price of electricity. Electricity is sold for immediate use in the wholesale spot market; the spot price fluctuates with the marginal cost of power throughout a given. Under flat-rate pricing, retail providers receive a fixed amount of revenue regardless of changing costs they face from the wholesale spot market. By allowing the retail price that electricity customers face to follow spot prices, retail providers provide themselves with a guarantee of revenues and less volatility in costs.

Previous research emphasizes who would most likely profit from RTP adoption, but does not address what types of customers voluntarily choose to be on RTP. I have access to a unique, new dataset gathered by the Texas electric grid operator (ERCOT) from retail providers in 2008 with information on which customers pay time-varying rather than fixed prices. I econometrically estimate the types of commercial and industrial firms that are likely to “sign up” for time-varying prices. This has important implications for the design of both deregulated electricity markets and policies that seek to increase the amount of electricity generated with renewable sources of energy.

The importance of knowing what types of customers are on RTP stems from technological advances in electricity metering and government support of renewable sources of energy. ‘Smart meters’ are now capable of measuring small intervals of consumption and relaying the data back to the provider. As more smart meters are installed across Texas and the U.S., RTP adoption will also expand. State requirements for greater use of renewable sources of energy, or renewable portfolio standards (RPS) have increased the need for generation of renewable energy. However, intermittency issues continue to stunt the growth of renewable energy generation. The unreliability of these sources during peak hours makes RPS difficult to meet. RTP shaves load during peak hours, putting more reliability in renewable sources of energy. In fact, RTP has the potential to reduce intermittency problems in any hour by offering a means to reduce demand when intermittent generation sources do not produce.

As the electricity market expands with increased adoption of RTP, understanding what types of customers will choose RTP contracts is of great interest to utility providers, policy makers and businesses contemplating RTP adoption. My research gives insight into how the expansion will proceed in the coming years. I look into the types of commercial and industrial customers likely to adopt RTP based on total hourly consumption, load profile, geographical location and industry type. I find that customers with greater total hourly consumption are more likely to be on RTP. Customers with more 'peaky' load profiles are also less likely to be on RTP. Customers in south and west Texas have a greater probability of being on RTP than customers in Houston. I also study whether customers on RTP decrease consumption on hot summer days when electricity is scare. It is important to know whether RTP customers are responsive to supply shifts because this shows whether RTP is effective.

CHAPTER II

DATA AND MODELS

Data

The public utility commission of Texas (ERCOT) gathered my data set from electricity retail providers through surveys. ERCOT is unique in that its customers choose to sign flat-rate or time-varying contracts as opposed to facing regulator-imposed tariffs. Consequently, this data provides insight into who actually chooses to sign RTP contracts. The customers with flat-rate pricing represent the control group in this analysis.

My data set contains 8,000 commercial and industrial electricity customers in Texas. I have the electricity consumption of every customer for every fifteen minute interval over the period of September 30, 2007 to September 30, 2008. The aggregation of this consumption data allows me to form variables about the spread of consumption of each customer and their total consumption. One group of the 8,000 customers faced flat-rate pricing and the other group faced time-varying pricing (RTP).

Model one: Who is on real-time pricing?

The first question I address is who voluntarily chooses to sign RTP contracts. In order to explain this question, I econometrically estimate the equation:

$$RTP_i = \beta_0 + \beta_1 \text{ total consumption}_i + \beta_2 \text{ location}_i + \beta_3 \text{ load profile}_i + \beta_4 \text{ industry}_i + \varepsilon_i$$

where RTP is a dummy variable for whether a customer is on RTP or not; total consumption is the total hourly consumption; location is the geographical location; load profile is the spread of consumption; industry is the industry type; and ε is the error term. These variables each in part describe the variation in whether or not customers are on RTP. I use simple and multivariate regressions of this linear probability model to determine the types of customers more likely to sign RTP contracts.

The first variable in my regression model is the total amount of energy they consume which reflects how large of an energy consumer the customer is. The variable total consumption is average hourly consumption across all consumption hours of my data set. Total consumption is related to the operations of the firm. Energy intensive firms (such as manufacturing firms) have higher consumption simply due to the nature of their industry as compared to less energy intensive firms (such as law firms). The question of interest is whether energy intensive firms are more likely to be on RTP than less energy-intensive firms. The magnitude of the social cost of inefficient electricity pricing is likely to be driven by the large, energy-intensive firms. Thus, it is important to know if these large customers are on RTP or on less efficient flat rate pricing. If larger consumers are on RTP, there is potential for reduction in total consumption and efficiency gains as well as reduced emissions if the electricity used is generated from fossil fuels.

The second variable in my regression model is geographical location; it shows which areas are more receptive to RTP. I measure geographical location with congestion management zone codes which correspond to sections of the Texas transmission grid. The four transmission areas of Texas are North, South, West and Houston. Figure 2 displays the zonal map of ERCOT. Certain areas can be more receptive to RTP due to a variety of factors including the network of transmission lines, city laws and city type (rural, urban, etc.) of the area. For example, west Texas contains a great amount of wind generation. Knowing that RTP is more likely to be adopted in west Texas is good news for wind generation because RTP provides increased confidence in renewable generation and thus more generation from renewable sources of energy.

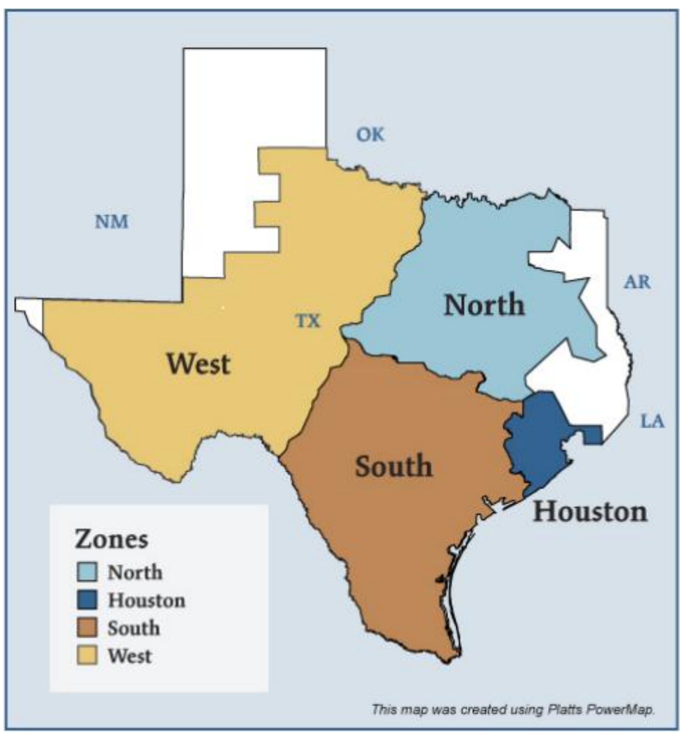

Figure 2. Texas (ERCOT) Electric Market Zones
Source: Adapted from www.ferc.gov/oversight 2010.

The third variable in my regression model is a measure of daily variation (or ‘peakiness’) of a customer’s daily electricity consumption. Peakiness refers to how volatile a customer's swings in consumption are throughout a given day. I analyze the consumption spreads of RTP customers and the control group -- fixed-price customers -- in order to determine how 'peaky' the customers from each group are. Each firm can vary in its ‘peakiness’—it can have a flat load as depicted by the brown line in Figure 3 or a peaky load as depicted by the red and blue lines. The red line shows a typical firm’s load profile which varies directly with the marginal cost of electricity. The blue line shows an atypical firm’s load profile which varies inversely with the marginal cost of electricity. That is, the firm’s consumption is peaky during off-peak periods when the marginal cost of electricity is low.

Periods of peak demand represent a serious problem for electricity retailers who supply electricity to businesses and people. High demand periods strain the electricity grid and force retailers to increase supply in order to meet demand. Retailers must purchase expensive generation units to supply enough electricity. The two potential consequences are rolling blackouts and massive increases in production costs. Generators incur significant production cost increases during peak periods because high cost “quick start” generators are relied on to meet demand. So peak load can have severe effects on the electricity grid, harming both consumers and producers. Thus, understanding how ‘peaky’ a customer is allows us to look at their contribution to the stress placed on electricity grids during peak periods.

Load profile can be measured in two ways: by individual firm and by the entire system. To measure peakiness on the individual level, I calculate the difference in the maximum hour of consumption from the minimum hour of consumption in a given day regardless of when those hours are in the day. This measure does not differentiate between the blue and red lines; it simply expresses how peaky a customer is relative to a customer with a flat load profile (the brown line).

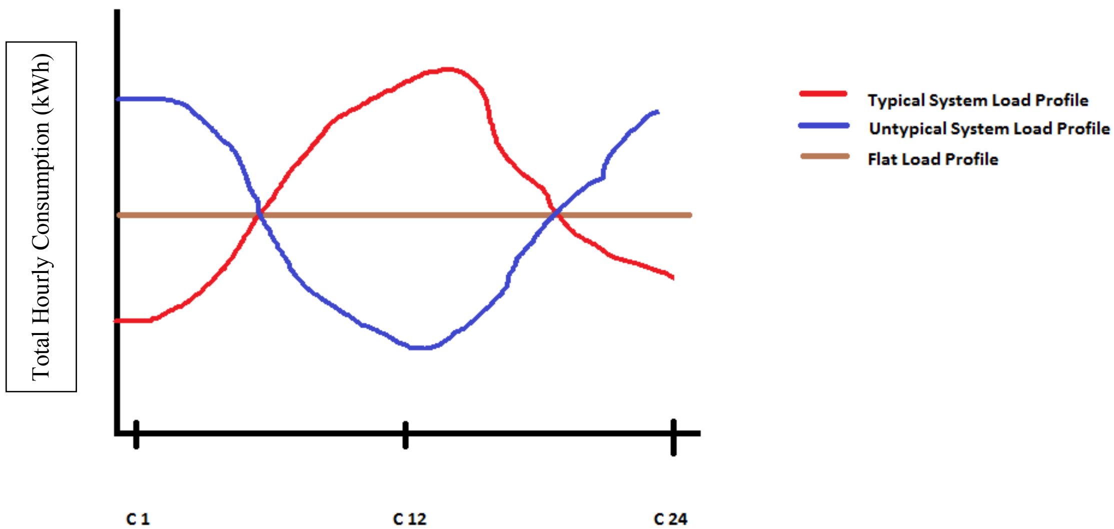

Figure 3. Stylized Load Profiles

From a system wide perspective, peakiness is measured by the difference between the peak and trough of the entire system. Figure 4 depicts the aggregate load profiles for the entire group of RTP customers and the entire group of flat rate customers. Customers on RTP have an hourly daily peak that is 9.6% higher than the daily trough. However, those not on RTP have an hourly peak 44.5% higher than the trough. The red line in Figure 3 represents a stylized version of a typical system load profile. To measure peakiness on the system level I calculate the difference between consumption periods 17 and 3 (5 PM and 3 AM) for the entire system. Thus, I can estimate how peaky a customer is relative to the peakiness of the entire system. Understanding the peakiness of each customer allows estimation of how effective RTP can be. That is, how much peak demand during system peak periods can be reduced.

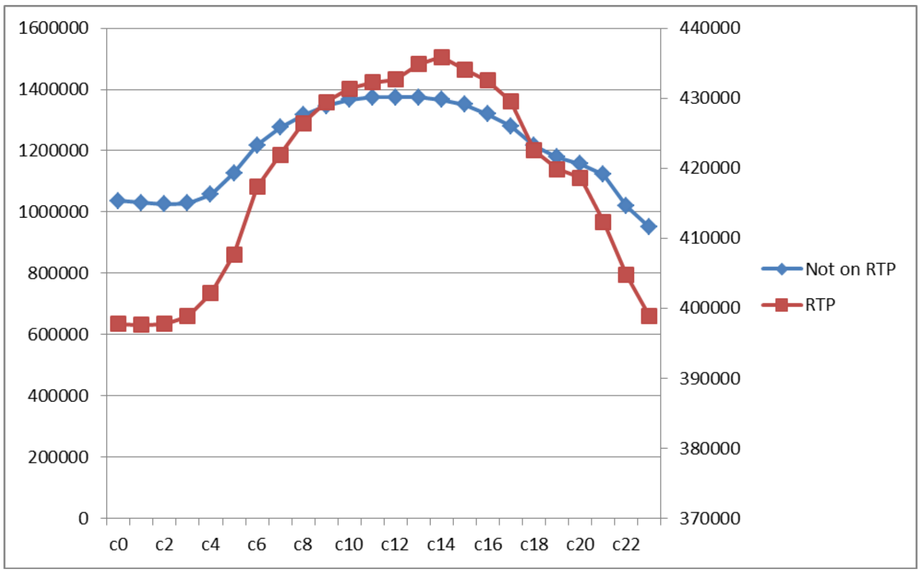

Figure 4. System Load Profiles

Source: Author Calculations from Consumption Data from ERCOT.

The fourth variable in my regression model is industry type. Each ESIID or electricity meter of my data-set has a corresponding North American Industry Classification System (NAICS) code that the U.S. government uses to classify industries for statistical purposes. Each digit of the code provides an additional level of specificity to the industry type. I have used a dummy variable for industry type at the two digit NAICS level in my regression analysis. Table 1 lists all of the industries included in my data set with their corresponding two digit NAICS code. Industry type gives understanding to the types and intensity of operations of various industries and thus the electricity consumption to facilitate those operations.

Table 1. Industries and Corresponding NAICS Codes at the Two Digit Level

Industry	**NAICS Code**
Agriculture, Forestry, Fishing and Hunting	11
Mining, Quarrying, & Oil/Gas Extraction	22
Utilities	23
Construction	31
Manufacturing	32
Wood Product Manufacturing	33
Metal Manufacturing	42
Wholesale Trade	44
Retail Trade	45
Sporting Goods, Hobby, Book & Music Stores	48
Transportation & Warehousing	49
Postal Service	51
Information	52
Finance & Insurance	53
Real Estate, Rental & Insurance	54
Professional, Scientific & Technical Services	55
Management of Companies & Enterprises	56
Administrative, Support, Waste Management & Remediation Services	61
Educational Services	62
Healthcare & Social Assistance	71
Arts, Entertainment & Recreation	72
Accommodations & Food Services	81
Other Services (except Public Administration)	82
Public Administration	92

Source: www.census.gov/naics/.

Model two: Evidence of consumer response to real-time pricing

One criticism of RTP is that customers should not be subjected to extremely high prices during peak periods such as summer heat waves because they cannot respond. So my second question of interest is whether RTP customers respond to higher prices. During a period of hot weather, it can be assumed that firms use more energy for such things as air conditioning whether they are on RTP or flat-rate pricing. However, RTP customers face an increasing price during peak periods while fixed-rate customers face the same constant price. If during hot weeks RTP customers increase consumption at a slower rate the flat-rate customers, RTP is successful in reducing peak demand even during periods when it seems difficult to reduce consumption.

I use two adjacent five day weeks in August 2008 to analyze whether RTP customers increase consumption at a slower rate than flat-rate customers during peak periods. One week contained more moderate temperatures and the other week contained significantly higher daily average temperatures. I use two adjacent weeks so that I can make a comparison of consumption differences without having differences in other aspects such as production processes and season. For example, if I were to compare the hottest week in July with the coldest week in January, I couldn’t compare the difference in consumption between the two weeks because there would be a host of other differences. By using two adjacent weeks I am able to almost hold constant all other differences because although there might be slight differences in production between the two adjacent weeks, the differences will be miniscule.

CHAPTER III

RESULTS

Results for model one

In order to determine what types of electricity customers voluntarily choose RTP contracts, I regress a variety of characteristics on whether a customer is on RTP or not. The characteristics of interest are total consumption, location, load profile and industry type.

I first estimate who is on RTP using each characteristic separately. The simple regression results are reported in Tables 3 and 4 of the Appendix. The standard errors of each estimate are reported below the estimates in parenthesis. Asterisks (*) denote significance at the ten percent significance level and plus signs (+) denote significance at the five percent significance level. Table 2 displays the summary statistics of the variables used in the regression analysis. Customers in the north zone of the transmission grid are .0125 less likely to be on RTP than customers in Houston. However, customers in the west and south are more likely to be on RTP than Houston customers; western customers have a .0129 greater probability and southern customers have a .0138 greater probability than Houston customers. A one standard deviation increase in total hourly consumption increases the probability that a customer is on RTP by .1002. So, larger consumers are more likely to be on RTP than flat-rate pricing holding nothing else constant. This has great potential for reducing consumption.

Table 2: Summary Statistics for Variables

Variables	Observations	Mean	Standard Deviation	Min	Max
RTP	8745	0.14	0.35	0	1
Total Consumption	8569	969.14	4277.51	0	187365.2
Location- North	8481	0.43	0.5	0	1
Location- South	8481	0.08	0.27	0	1
Location- West	8481	0.1	0.3	0	1
Daily Maximum Consumption Minus Minimum	8569	278.88	1713.68	0	104677.4
Consumption hour 17 minus hour 3	8569	104.95	856.1	-65949.5	4182.57

Source: Author's calculations from Consumption Data from ERCOT

The simple regression estimations for load profile are inconsistent. A one standard deviation increase in load profile measured by the difference in hour 17 and hour 3 decreases the probability that a customer is on RTP by .0317. However, a one standard deviation increase in load profile measured by the difference in the maximum and minimum hours of consumption increases the probability that a customer is on RTP .0355.It is inconclusive whether more peaky or less peaky customers are more likely to be on RTP using simple regressions. Multivariate regressions provide a more consistent and clear result.

Compared to the excluded group (Agriculture, Forestry, Fishing and Hunting), the industries most likely to be on RTP are: Sporting Goods, Hobby, Book and Music Stores, Retail Trade, Transportation and Warehousing, Wood Product Manufacturing, and Finance and Insurance. These industries are highlighted in Table 3. These are followed by Other Services (except Public Administration), Wholesale, Trade, Manufacturing, Postal Service, Professional, Scientific and Technical Services, Healthcare and Social Assistance, and Administrative and Support and Waste Management and Remediation Services. All other categories have sufficiently few observations so I cannot develop precise estimates of the fraction of customers on RTP.

The multivariate regressions of the model display similar results in Appendix Table 3. In these regressions, I analyze the effect of one characteristic while holding constant the value of all other characteristics. This allows me to do *ceteris paribus* comparisons of the effect of each characteristic on the probability of being on RTP. Large consumers are still more likely to be on RTP; a one standard deviation increase in consumption, holding load profile and location constant, increases the probability of being on RTP by .1062. In fact, holding all else constant, larger consumers are more likely to be on RTP. A one standard deviation increase in total consumption increases the probability of being on RTP by .1233.

Customers in the south are 4% more likely to be on RTP and customers in the west are 5% more likely than customers in Houston, holding load profile and total consumption constant. Holding all else constant, customers in the south have a 7% greater chance of being on RTP than those in Houston.

In the multivariate regression analysis, peaky consumers are less likely to be on RTP using both measures of peakiness (the difference between maximum and minimum and hour 17 and hour 3). Holding total consumption and location constant, a one standard deviation increase in load profile (the difference between hour 17 minus hour 3) decreases the probability of being on RTP by .045. Holding all else constant, a one standard deviation increase in load profile measured by the difference in the maximum and minimum hours of consumption decreases the probability of being on RTP by .0481. So, more peaky firms are less likely to be on RTP.

Throughout all of the regressions, the industry types with the greatest probability of being on RTP remained statistically significant throughout all of the regressions. These industries are highlighted in Table 5. I conclude with confidence that all of these industries are more likely to be on RTP than the other industries represented in the sample compared to the excluded group.

Results for model two

One objection that some people have to RTP is that customers should not be subjected to extremely high prices because during peak periods such as summer heat waves, they cannot respond. However, my research shows that customers do indeed respond even during peak periods. Non-RTP customers consume 5.4 more kWh than they did during the cooler week. And RTP customers only consumed 3.38 more kWh than they did during the cooler week. I find that relative that those not on RTP, those on RTP reduce consumption by 2.03 kWh. The sign of the point estimate is consistent with customers on RTP increasing demand by less during hot weeks, but the coefficient is not precisely estimated.

CHAPTER IV

CONCLUSIONS AND POLICY IMPLICATIONS

Technological advances in electricity metering and government support of renewable sources of energy have led to greater adoption of RTP in electricity markets. State requirements for greater use of renewable sources of energy, or renewable portfolio standards (RPS) have increased the need for generation of renewable energy. However, intermittency issues continue to stunt the growth of renewable energy generation. RTP shaves load during peak hours, putting more reliability in renewable sources of energy. As the electricity market expands with increased adoption of RTP, understanding what types of customers will choose RTP contracts is of great interest to utility providers, policy makers and businesses contemplating RTP adoption.

My results show that larger consumers are more likely to be on RTP. Larger consumers have the potential to make significant reductions in their consumption. Thus, there are large efficiency gains to be realized. If the electricity generated for these consumers is from fossil fuel generation, reduction of total consumption will also lead to reduced emissions. A less promising result is that more peaky customers are less likely to be on RTP. Since RTP helps reduce peak demand and peaky customers are less likely to choose RTP contracts, there is a great amount of efficiency gains still to be realized. In order to realize these gains, retail providers could supply more incentives for customers to adopt RTP. For example, retail providers could ensure some price security by not allowing price to increase over a certain threshold.

My results also show which areas in Texas are more receptive to RTP. The south and west are most receptive compared to Houston. The great amount of wind generation in west Texas points to the potential of RTP providing reliability in wind generation for electricity markets. I also find the industries most receptive to RTP. These industries are both in the commercial and industrial sectors.

Real-Time Pricing provides a solution to the inefficiency of flat-rate pricing. As RTP adoption spreads across Texas, the expansion of RTP is of great interest to policy makers, utility providers and businesses. I predict how the expansion will occur using econometric analysis. I also find that RTP customers actually respond to higher prices during peak periods. Customers are indeed responsive and thus, RTP is efficient *and* effective.

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APPENDIX

Table 3: Simple Regressions of Total Consumption, Location, and Load Profile

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Average Hourly Consumption (kwh)	0.00000821*			
	(0.000000953)			
North		-0.01		
		(0.01)		
South		0.01		
		(0.01)		
West		0.01		
		(0.01)		
Consumption Hour 17 minus 3			-0.0000183*	
			(0.00000473)	
Daily Maximum Consumption Minus Minimum				0.00000725*
				(0.00000235)
Constant	0.16*	0.13*	0.17*	0.16*
	(0)	(0.01)	(0)	(0)
N	7555	8551	7555	7555
R^2	0.0096	0.0003	0.0018	0.0011

Table 4: Simple Regressions by Industry

Variables	**(5)**
Mining, Quarrying, and Oil and Gas Extraction	0.05
	(0.1)
Utilities	0.07
	(0.11)
Construction	0.03
	(0.08)
Manufacturing	0.18
	(0.12)
Wood Product Manufacturing	0.23*

	(0.08)
Metal Manufacturing	0.08
	(0.08)
Wholesale Trade	0.16+
	(0.08)
Retail Trade	0.26*
	(0.08)
Sporting Goods, Hobby, Book and Music Stores	0.27*
	(0.08)
Transportation and Warehousing	0.26*
	(0.09)
Postal Service	0.17
	(0.12)
Information	0.04
	(0.09)
Finance and Insurance	0.20+
	(0.08)
Real Estate and Rental and Insurance	0.05
	(0.08)
Professional, Scientific and Technical Services	0.14
	(0.08)
Management of Companies and Enterprises	0
	(0.2)
Administrative and Support and Waste Management and Remediation Services	0.13
	(0.09)
Educational Services	0.01
	(0.08)
Healthcare and Social Assistance	0.14
	(0.08)
Arts, Entertainment and Recreation	0.05
	(0.1)
Accommodations and Food Services	0.08
	(0.08)
Other Services (except Public Administration)	0.17+
	(0.08)
Public Administration	0.02

	(0.09)
Other	0
	(0.33)
Constant	0
	(0.07)
N	1935
R^2	0.0633

Table 5: Multivariate Regressions

Variable	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
Constant	0.12*	0.12*	0	0.01	0	0	-0.01	-0.01
	(0.01)	(0.01)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
N	7372	7372	1833	1934	1833	1833	1833	1833
R^2	0.0136	0.0148	0.0732	0.0635	0.0712	0.0686	0.0766	0.0777
Average Hourly Consumption (kwh)	0.0000087*	0.0000106*	0.00000613*				0.0000058*	0.0000101*
	(0.00000102)	(0.00000115)	(0.00000203)				(0.00000204)	(0.00000257)
North	0.03*	0.03*		-0.02			0.02	0.03
	(0.01)	(0.01)		(0.02)			(0.02)	(0.02)
South	0.04+	0.04+		0.04			0.07+	0.07+
	(0.02)	(0.02)		(0.03)			(0.03)	(0.03)
West	0.05*	0.05*		-0.01			0	0
	(0.01)	(0.01)		(0.04)			(0.05)	(0.05)
Consumption Hour 17 minus hour 3	0.00000259				-0.0000715+		-0.0000648+	
	(0.00000506)				(0.0000315)		(0.0000316)	
Daily Maximum Minus Minimum Hourly Consumption		-0.00000833*				0		-0.00000984+
		(0.00000282)				(0.00)		(0.00000395)
Mining, Quarrying, and Oil and Gas Extraction			0.04	0.04	0.07	0.05	0.07	0.05
			(0.10)	(0.10)	(0.11)	(0.10)	(0.11)	(0.11)
Utilities			0.07	0.06	0.07	0.07	0.06	0.06
			(0.12)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)
Construction			0.02	0.02	0.04	0.03	0.02	0.03
			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Manufacturing			0.18	0.17	0.18	0.18	0.17	0.17
			(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)

Wood Product Manufacturing			0.23*	0.23*	0.25*	0.25*	0.22+	0.22+
			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Metal Manufacturing			0.08	0.07	0.09	0.08	0.09	0.08
			(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Wholesale Trade			0.16	0.15	0.18+	0.17+	0.17	0.16
			(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Retail Trade			0.28*	0.25*	0.29*	0.28*	0.28*	0.28*
			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Sporting Goods, Hobby, Book and Music Stores			0.27*	0.26*	0.29*	0.28*	0.28*	0.28*
			(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Transportation and Warehousing			0.26*	0.26*	0.27*	0.26*	0.27*	0.27*
			(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
Postal Service			0.18	0.15	0.18	0.18	0.17	0.17
			(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Information			0.04	0.03	0.06	0.04	0.05	0.04
			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Finance and Insurance			0.21+	0.20+	0.23*	0.22+	0.22+	0.21+
			(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Real Estate and Rental and Insurance			0.05	0.04	0.06	0.05	0.06	0.05
			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Professional, Scientific and Technical Services			0.15	0.14	0.16+	0.15	0.16	0.15
			(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Management of Companies and Enterprises			0	-0.01	0.03	0	0.03	0.01

			(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Administrative and Support and Waste Management and Remediation Services			0.14	0.13	0.15	0.14	0.15	0.14
			(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)
Educational Services			0.01	0	0.02	0.01	0.01	0.01
			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Healthcare and Social Assisstance			0.14	0.13	0.15	0.14	0.15	0.14
			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Arts, Entertainment and Recreation			0.05	0.04	0.06	0.05	0.06	0.06
			(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
Accommodations and Food Services			0.09	0.07	0.1	0.09	0.09	0.08
			(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)
Other Services (except Public Administration)			0.18+	0.16	0.19+	0.19+	0.19+	0.18+
			(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Public Administration			0.02	0.01	0.03	0.02	0.02	0.02
			(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)
Other			0	-0.01	0	0	0.01	0.01
			(0.33)	(0.33)	(0.33)	(0.34)	(0.33)	(0.33)

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