Three Essays on Price and Weather Responses of Commercial and Industrial Customers in Hawaii

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Abstract

The electricity market is now facing a crossroad, due to rises in new technologies such as energy efficient appliances, renewable energy systems, and smart meters. The introduction of renewable energy resources has put pressure on the traditional grid. The energy market must undergo drastic changes in terms of demand and supply side management to meet the rise in new technologies. This includes new pricing schemes to signal customers to avoid consuming energy during peak times, demand response programs, and energy efficiency. However, increasing levels of behind the meter technology has made customer demand less transparent, and harder to implement demand side programs without fully understanding how consumers respond to prices or weather changes. Hence, there is increased need to improve existing models of energy demand modeling. Because we do not know how commercial and industrial (C&I) sector demand, this study tries to characterize consumer energy demand for the C&I sectors. Through the analysis this paper finds that certain customers are indeed more price responsive than others, certain sectors are temperature sensitive, and there are winners when an alternative pricing structure is introduced. This paper makes several contributions to the existing literature. First, consumption behavior of sectors within the C&I sector is unclear as studies on the effects of price energy consumption of C&I sectors are sparse when the share of end use electricity is significantly larger than the residential sector. Hence, C&I customers are ideal targets for demand side management practices because they have a larger contribution to the system compared to residential customers. Second, this paper reveals which types of customers experience benefits in the form of decreased bills under marginal cost pricing. Finally, this paper helps understand how C&I customers alter their electricity consumption to a response in temperature and price.

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Chapter 1

Electricity Price Response by Commercial and Industrial Customers under Rate Schedule Change

1.1 Introduction

Hawaii has experienced significant growth of customer distributed energy resources (DER) due to its high electricity prices and ambitious green energy policies such as Renewable Portfolio Standards (RPS) and income tax credits. As more DERs are integrated to the electric grid, system operators find it challenging to match energy supply with demand. The intermittent nature of DER such as photovoltaic (PV) systems has increased the uncertainty in predicting future customer demand. Hence, the introduction of DER has prompted the need to better grasp current and future energy demand. Customer price response to incentive based tariffs can serve as an essential input to understanding consumer behavior. For example, characterizing energy consumption can assist system operators in matching electricity supply with demand, identifying potential customers for DR programs, and increasing grid reliability. The effectiveness of pricing schemes lies in its ability to induce individuals to alter their behavior by reducing demand during peak hours. Customer response to dynamic pricing has been a well researched topic by scholars, and their findings has provided further insight on consumption behavior. Such dynamic pricing schemes include: critical peak pricing(CPP), real-time pricing (RTP), and time-of-use (TOU) pricing. This paper attempts to model energy consumption behavior of commercial and industrial (C&I) customers by examining their response to price without exploiting dynamic pricing schemes. Like many other states, Hawaii does not have time varying pricing programs in effect because of the lack advanced metering equipment in place that accommodate pricing schemes such as real-time pricing. Moreover, these types of pricing schemes face implementation and transaction costs, which include costly metering and accounting systems for billing and settlement purposes (Woo, Horii, & Horowitz, 2002). Given the circumstances, understanding consumer response to dynamic price changes becomes complicated due to lack in mixed response drivers such as real-time-pricing tariffs. Nonetheless, the rate pricing structure in Hawaii can provide an understanding of how price elasticity of demand differs for distinct commercial and industrial (C&I) groups. The model we estimate examines the influence of rate schedule "switching" on price elasticity. Specifically, customers are placed under one of three rate schedules based on their monthly peak (kW) and/or kWh usage. Switching between rates occurs when energy consumption surpasses a certain threshold. The change in energy prices when customers switch rate schedules can provide an insight to customer price response. Our hypothesis is that customers who have experienced a rate switch are more price elastic relative to customers who have never experienced a switch. The estimated model can be used to evaluate consumption behavior under different rate schedules. To prove this, we leverage the rules that determine rate schedule placement. The kilowatt cutoffs that determine rate schedule placement are 25 kilowatts and 300 kilowatts. The two values serve as thresholds (25 kW and 300 kW) and play a role as identification in our analysis. Specifically, C&I customers who have peak demand close to the 25 or 300 kilowatt thresholds may have an incentive to consume electricity different than customers who are not. This is because consuming right below either threshold generates the threat of being bumped up to a rate schedule with a higher bill charge. Furthermore, to address several estimation issues, such as customer self-selection, we use a group of customers who are exempt from the rules of rate schedule placement as a control group. We use panel fixed effects regression to identify rate switching impacts on price elasticity of electricity demand. Finally, this paper presents quantitative evidence to support our hypothesis that customers who switch rates are more responsive to price than those who have not. Findings can be utilized by the utility and regulators to better understand customer price response. In addition, forecasts of energy demand can be improved via understanding of customer behavior. Hence, regulators can generate estimates of future capacity requirements in the C&I sector.

There is lack of studies in the literature that research customer price response to rate schedule changes. Previous literature focuses on the effectiveness of dynamic electricity pricing schemes in reducing peak demand, such as RTP and CPP. Among economists and policy makers there is a widespread agreement of the benefits of RTP relative to other schemes. Borenstein shows the wealth transfers that occur when electricity systems change from the current simple-retail structure to RTP structure. He finds that there are significant wealth transfers when changing to a RTP structure, but there is likely to be a role for programs that mitigate the wealth transfers from RTP while still achieving the efficiency gains (Borenstein, 2007). Moreover, advocates for RTP argue that it is a crucial component of an efficient restructured electricity market. A study by Borenstein (2005), which estimates the long-run societal gains from RTP, finds that RTP would lower peak electricity production and reduce the use of low-capital-cost/high-variable-cost peaker generation. Such programs can generate benefits for the utility and for some consumers. For example, supplying energy at times when peak demand is high can be expensive for the utility. Electricity is supplied by a mix of generating technologies such as wind, solar, coal, oil and natural gas plants. Renewable energy is considered a low marginal cost technology with natural gas and coal next in terms of low cost. On the other hand, oil burning power plants face higher marginal costs and low fixed costs (Boomhower & Davis, 2017). Sufficient generation capacity needs to exist for the utility to match the supply with demand at every moment in time. In the long run, high levels of peak demand require the utility to create additional generation capacity. Hence, shaving customer peak demand will not only allow the utility to avoid starting up higher marginal cost plants, but also dodge the costs of additional generating capacity (Blonz, 2016). On the other hand, research on customer response of CPP, which charges higher rates during peak demand times, shows that residential high-use customers indeed respond significantly in kW reduction when faced with higher prices during specific time intervals of the day than low-use consumers (Herter, 2007). While most studies focus on understanding price response for residential customers, research on the behavior of C&I customers are lacking even though they have a higher share of end use energy consumption than do residential customers(EIA, 2014). However, limited studies on C&I customer response to price find that peak pricing indeed has an impact on electricity consumption. A study by (Blonz, 2016) finds that peak pricing reduces electricity consumption for non-coastal establishments by 13.4 percent on event days and predicts that peak demand programs will reduce peak demand by 118 MW among small C&I customers if fully implemented by 2018. The study concludes that programs will reduce the need to create specialized power plants that are constructed with the sole purpose of generating electricity during the highest demand hours of the year (Blonz, 2016). As seen from the literature, most studies exploit dynamic pricing schemes to examine decreases in peak demand when electricity prices increase. Our paper, aims to tackle customer demand modeling from a different angle. Rather than investigating peak reduction, we estimate the price elasticity of certain customer groups within the C&I sample.

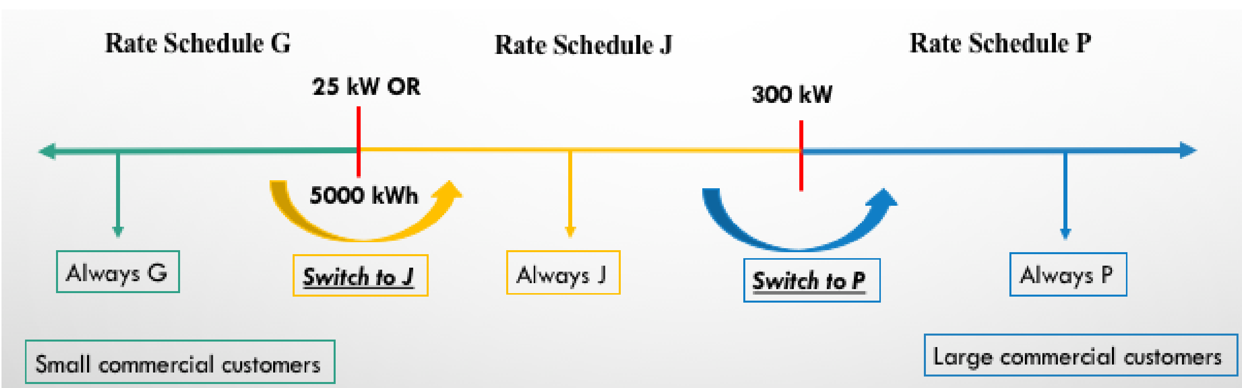
This paper makes three important contributions to the existing economics literature. First, there is limited academic research that studies how rate structures affect energy consumption. Our paper investigates how the elasticity of C&I sectors differ under alternative rate schedules. Since customers who experience rate switching face changes in bill rates, we predict that switching induces customers to become more aware of their energy consumption; just as CPP or RTP induce customers to use less energy at certain time slots. As stated previously, Hawaii does not have dynamic pricing, and customer price response to changes in rate schedules will be exploited to explain customer behavior. In addition, existing literature focuses on price response of residential consumers rather than commercial and industrial (C&I) customers when the portion of end use electricity consumption is higher for C&I customers combined. Hawaiis electricity consumption by sector shows that two-thirds of electricity is consumed by C&I consumers EIA (2014). This makes the C&I sectors response to prices important for future energy policy. Second, this paper contributes to the literature on price elasticity of demand for commercial and industrial (C&I) customers. Research on elasticity of demand in the for C&I sector electricity consumption is a mixed bag with elasticities ranging from -0.1 to -0.5 Bjørner, Togeby, & Jensen (2001), depending which methods are used. Bjørner et al. (2001) finds that when comparing repeated cross-sections estimates and fixed effect panel data estimates, price elasticities are considerably lower in the latter case when utilizing the panel nature of the data. Furthermore, using a logit linear specification, Elkhafif (1992), finds that the short run elasticity for industrial consumers to be -0.147. Bernstein & Griffin (2006) show elasticity estimates of commercial sector ranging from -0.5 to -0.1 using a state level analysis. In addition, using region level analysis, they find that the commercial sector has a price elasticity of demand for electricity from -.3 to -.15 Bernstein & Griffin (2006). Due to similarity in data with Bjorn, the panel fixed effects regression will be utilized in this paper. However, Bjorn bases estimates on reported electricity consumption from an energy industrial survey. The disadvantage of survey data as indicated in the paper by Bjorn is the problem of missing data. However, our paper utilizes raw consumption data that was recorded by a meter installed at a customer site. Finally, we address the problem of endogeneity in customer decision. This is done by exploiting the nature of "grandfathering." Grandfathered customers are establishments which are exempt from the rules that govern rate placement. Specifically speaking, these customers are not penalized for having high peak demand. These customers serve as a control group when comparing price response with those who have switched rates.

The rest of the paper is organized as follows: Section 2 discusses Hawaiian Electric Companys commercial and industrial rate structure in detail. Section 3 outlines the data used in the analysis. Section 4 describes the baseline empirical strategy without addressing the endogeneity issue. Section 5 presents the baseline results; section 6 presents describes the identification strategy for grandfathered customers while addressing the endogeneity issue and section 7 concludes.

1.2 Background of Hawaiian Electric's Customer Rate Structure

The Hawaiian Electric Company electricity rate tariffs for commercial and industrial (C&I) customers consist of three distinguished schedules that have been in effect since March 1, 2011. The pricing structure is constructed by three rate schedules that have different fixed, energy, and demand charges. C&I customers are categorized under G (General Service Non-Demand), J (General Service Demand) or P (Large Power Service) rate schedules. Figure 1.1 illustrates the spectrum of rate groups that face varying fixed, energy, and demand charges. As illustrated in figure 1.1, the determinants of schedule placement are dependent on monthly peak demand or kWh usage of the customer. Twenty-five kilowatts and 300 kilowatts are the two cutoffs that determine rate placement. Power loads less than or equal to 5000 kilowatt hours (kWh) per month, and less than or equal to 25 kilowatts are categorized under rate schedule G. Power loads that exceed 5000 kilowatt hours per month or exceed 25 kilowatts three times within a twelve-month period but are less than 300 kilowatts per month are categorized under rate schedule J. Finally, power loads equal to or greater than 300 kilowatts are categorized under schedule P. Small C&I customers are located on the left end of the spectrum and consists of customers who are categorized as always rate G or J as seen from the figure. On the other hand, large commercial customers are located on the right side of the spectrum with monthly kilowatt ranging anywhere from 300 kilowatts and above. In addition, there are customers who experience rate switching. The reason for rate switching is not observed in the data. However, the date of rate switching is known. Switching between rate schedules takes place when a customers peak demand (in kilowatts) exceeds either thresholds. Switching to a rate schedule with a lower demand charge (moving from rate J to G, for example) occurs when a customer reduces their monthly less than or equal to 5,000 kilowatt hours per month *and* less than or equal to 25 kilowatts for 12 consecutive months. Similar rule applies for customers to move from rate P to J except customers are only required to fulfill the kW demand requirement for 12 consecutive months. On the other hand, placement to a rate with a higher demand charge (rate J to P, or G to J) only occurs when a customer exceeds either threshold three consecutive months within a 12 month period. Thus, switching to a rate schedule with higher demand charge is easier than returning to a lower one since it only takes three months of peak demand over the threshold to be bumped up to a new rate schedule.

Figure 1.1: Rate Placement by monthly peak usage



Note: The illustration above presents the spectrum of possible placement of customers based on the month peak usage within a year. Hawaiian Electric Company has various rate schedules but only G, J, and P rates for commercial and industrial customers are taken into account in this analysis. Information are obtained from Hawaiian Electric's public website. https://www.hawaiianelectric.com/billing-and-payment/rates-and-regulations/hawaiian-electric-rates for more details.

In this paper, "rate groups" are groups that are segmented based on categories explained in figure 1.1, and should be distinguished from "rate schedule." For example, as per figure 1.1, customers who have never switched rates during the sample period are denoted with the name "always _." On the other hand, "switch to _" customers are those who have switched to a schedule with a higher demand charge. Hence, rate groups consist of a total of five groups: customers who are always in G, always in J, always in P, switched to J and switched to P, while the term "rate schedule" indicates the three rate schedules that determine the total amount of the bill a customer faces. It is important to note the differences because the analysis will be conducted on each rate group rather than each rate schedule.

Table 1.1: Monthly Bill Composition by Rate Category

Rate Category	Fixed Rate		Energy Charge	Demand charge
	Single Phase	Three Phase		
G (General Service Non-Demand)	$33	$61	21.3 cents/kWh	N/A
J (General Service Demand)	$60	$82	17cents/kWh	$11.69/kW
P (Large Power Service)	N/A	$350	14.9cents/kWh	$24.34/kW

Note: The table above presents the fixed rate (dollars per month), volumetric rate (cents/kWh), and demand charge (dollars per kW) for each rate category at Hawaiian Electric Company. These rates have been in place since 2012. Data are obtained from Hawaiian Electric's public website. https://www.hawaiianelectric.com/billing-and-payment/rates-and-regulations/hawaiian-electric-rates for more details.

Total bill consists of the fixed customer charge, volumetric energy charge, and demand charge. The component of a customer bill varies based on the rate schedule a customer faces. Customer charges differ between rate schedules, and table 1.1 presents the charges by rate. Energy charge per kilowatt hour is the highest for schedule G while the lowest is schedule P. Fixed charges are claimed monthly with schedule P having the highest fixed charge and G the lowest. Unlike residential customer rates, which are based on volumetric energy charges (cents/kWh) and a fixed customer charge, commercial rates include demand charges ($/kW) in addition to volumetric and fixed customer charges. Energy charges depend on total monthly power use while demand charges depend on maximum power used in a month. Demand charges are based on the customers peak demand (kW). The value of the demand charge is fixed every month as indicated in table 1.1, and the total amount charged depends on your monthly peak demand. Schedule G, for example, does not incur demand charge while schedules J and P are charged $11.69 and $24.34 per kilowatt respectively. Monthly effective rates (cents/kWh) are used as the price variable in our analysis and is equal to the base rate and other surcharges. Although the base rate does not change from month to month, the effective rates vary depending on the oil price. Figure 1.2 illustrates monthly effective rates from 2014 to 2017. General Service Non-Demand customers face the highest effective rate and Large Power Service customers face the lowest price per kWh. This may be counter intuitive but General Service Non-Demand customers face higher kWh charge because they do not have a high usage (kWh), while customers in rate P have very high usage.

Figure 1.2: Monthly Effective Rates (2012-2017)

Note: The figure above shows the changes in monthly effective rates (cents/kWh) from 2012 to 2017 for rate schedules G, J, and P. For more information on the definition of effective rates refer to the text. Effective rate information are obtained from Hawaiian Electric's public website. https://www.hawaiianelectric.com/billing-and-payment/rates-and-regulations/hawaiian-electric-rates for more details.

1.3 Data

1.3.1 Commercial and Industrial billing data

We rely on billing data from Hawaiian Electric Company (HECO) to estimate the empirical model. The data set consists of all C&I customers that have establishments on the island of Oahu, and are serviced between January 2012 to December 2017 by HECO, the sole energy provider on the island. Data was available from 2002. However, our analysis utilizes data from 2012 because of a rate case prior to 2012, which makes it difficult to compare the same customer over these dates. Monthly data obtained from the utility include: peak kilowatts, kilowatt hours consumed, the total electric bill, rate class, rate switching dates if the customer experienced switching, and billing start to end date.

This panel data set has an advantage that offers larger flexibility with respect to modeling the heterogeneity between companies. In addition, it is not necessary to impose strict assumptions on the uniformity of the estimated parameters as with cross-sectional data because companies are followed over time Bjørner et al. (2001). Furthermore, to simplify the analysis, we segment our sample further into two samples to distinguish between small business establishments from larger ones and conduct separate analysis for each. The reason for this is because large customers may have different consumption patterns than small businesses, and it may not make sense to compare elasticity estimates between the two types of customers. This will allow us to focus on the casual impacts of rate switching for customers who are close to the 25 kW and 300 kW peak thresholds.

The description of the two samples are described as below:

(Sample 1) Customers who have always been in rate G, customers who were in rate G but have experienced a rate switch to J, and customers who have always been in rate J. Customers who are categorized under schedule P have been omitted.

(Sample 2) Customers who have always been in rate J, customers who were in rate J but have experienced a rate switch to P, and customers who have always been in rate schedule P. Customers who are categorized under schedule G have been omitted.

It is important to note that customers who have always been in rate J are included in both samples.

Table 1.2 provides descriptive results by customer rate group. The table shows that customers who have always been in rate schedule G have a relatively lower bill total than those who have experienced a switch to J or have always been in J. This could be the case because customers in rate G do not face a demand charge. The table shows that customers who have switched to schedule J have an average monthly peak demand that is above but close to the 25 kilowatt threshold, at a mean monthly kilowatt usage of 45 kilowatts. Moreover, customers who have always been in rate P are very large customers who have a monthly peak demand that is far from the 300 kilowatt cutoff and consist of large hotels universities and hospitals. The last column in table 1.2 indicates the number of firms in each rate category. Customers who has always been in G do not face demand charge, hence, these customers do not have demand meters at their site.
Finally, table 1.3 shows summary statistics for a sample of customers who have PV systems. This table is included to illustrate how electricity consumption changes when PV systems are installed. Customers who have never switched and have always been in rate schedule J have the most PV systems installed. When comparing table 1.3 with 1.2, it can be seen that mean monthly peak load decreases when PV systems are installed, which is no surprise since daytime load most likely decreases when a customer installs PV.

Table 1.2: Summary Statistics of Rate Groups (Monthly Usage, 2012-2017)

	Consumption (000s kWh)		Peak Load (kW)		Bill($)		
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	# firms
Always G	1.0	1.2	.	.	333.9	364.2	38,597
Always J	23.6	39.8	72.1	227.5	6,741.3	11,733.4	8,097
Always P	418.8	424.7	845.9	774.6	107,884.1	108,503.5	385
Before switch to J	4.3	4.0	19.4	17.5	1,350.2	1,150.5	1209
Switch to J	12.3	25.2	43.5	175.2	3,594.8	7,595.8	1209
Before switch to P	104.7	82.0	282.9	144.8	29,110.7	22,914.4	156
Swtich to P	213.6	144.5	472.5	261.1	51,936.4	33,898.9	156

Note: The table above presents average monthly mean kWh, kW, and bill for each rate category. Standard deviation and number of firms are also presented. The sample includes billing data for all customers in Oahu from 2012 to 2017. Peak demand data for customers who have always been in rate G are not shown as they do not have demand meters installed at their site. Customers in rate G do not face a demand charge.

Table 1.3: Summary Statistics of Rate Groups for PV customers (Monthly Usage, 2012-2017)

	Consumption (000s kWh)		Peak Load (kW)		Bill($)		
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	# firms
Always G	0.35	1.38	.	.	0.22	0.25	110
Always J	19.0	27.0	61.6	60.9	5,708.2	7,274.8	553
Always P	258.3	627.2	638.8	76.7	67,577.6	12,279	55
Switch to J	7.0	12.5	32.8	56.7	2,783.9	3,789.1	13
Swtich to P	171.5	120.0	406.9	182.9	43,476.7	27,485	28

Note: The table above presents monthly mean kWh, kW, and bill for each rate category. Standard deviation and number of firms are also presented. The sample is restricted to customers who have PV from 2012 to 2017.

1.3.2 Weather data

Monthly average temperature is obtained from the National Oceanic and Atmospheric Administration (NOAA), which contains mean monthly temperature. Following the method used by Auffhammer & Aroonruengsawat (2011), temperature is included in a way that imposes a minimal number of functional form restrictions to capture potentially important non-linearities of the outcome of interest in weather. This is achieved by sorting each days mean temperature experienced by household i into one of the 10 temperature bins. In order to define a set of temperature bins, temperature distributions are sorted into percentiles and are used as the bins for sorting. The temperature distribution is then split into 10 bins. For each establishment, bin definition and billing period the number of days the mean daily temperature falls into each bin is counted.

1.3.3 Other data

To construct the final data set, we merge monthly effective rates and ownership of photovoltaic systems, which are provided by HECO. Data on PV system ownership includes customer name and information on the specific dates the system was installed. Effective rates are used as the price variable in my estimation and is obtained from HECO. Effective rates are the base rates adjusted for applicable surcharges and adjustments. Surcharges depend on oil price fluctuation. Hence, effective rates vary each month and is used as the price variable in the elasticity regression.

1.4 Identification and Empirical Approach

1.4.1 Baseline Approach

The nature of the pricing structure at HECO does not allow for the use of regression discontinuity (RD) approach since there is no clear cutoff for rate switching and the control group will consist of both establishments who have experienced a rate switch and those who have not. Fixed effects regression is ideal for panel data rather than micro cross section models of industrial energy consumption may be upward biased upward due to unobserved heterogeneity (Bjorn 2001). Each customer has a different date that they switched rate schedules and the analysis will be conducted accordingly to incorporate the time differences between customers. This section describes the empirical approach used to evaluate price elasticity and firm response to a change in rate schedules. This is a baseline model that exploits variation in the rate structure over time and across firms. Equation (1) is run separately for each rate category to estimate price elasticity of demand per group. Moreover, samples (1) and (2) are used for this analysis (explained in the data section above). However, estimation results will be presented separately for each sample. The baseline specification is as follows:

$$y_{it} = \beta_1 * ln(p_{t-1}) + \beta_2 * ln(p_{t-1}) * PV_{it} + \beta_3 * PV_{it} + \beta_p * D_{itp} + \alpha_y + \mu_m + \eta_i + \epsilon_{it} \tag{1.1}$$

where y_{it} is the log of the dependent variable of interest: electricity consumption (kWh) for establishment i in billing period t, and peak load (kW). The regression is run for each rate group, and the result will provide us with an elasticity, β_1, for each rate group (alwaysJ, alwaysP, alwaysG, and rate switchers). The variable p represents the log of monthly effective rate in period t. Consumers may react to lagged price rather than contemporaneous price because they receive their electric bills at the end of the month Ito (2014). Hence, the analysis uses one-month lagged prices. The volumetric rates vary by month and rate schedule. This price variation is used to estimate price elasticities. $price * PV$ is an interaction between PV dumour and effective rate, D_{pit} are binned weather observations, α_y is the year dummy, μ_m is the month dummy and η_i is the establishment specific fixed effect. Month and year dummies and firm fixed effects are included to control for contemporaneous shocks that affect electricity consumption common to establishments. As per Jessoe & Rapson (2015), the standard errors are clustered at the firm level to allow for correlation across all observations within a firm. Moreover, the PV dummy specifies the month that the customer PV installation took place, making it a time variant term. The identification variation comes from within-establishment variation in peak electricity demand by different rate groups (alwaysJ, alwaysP, alwaysG, and rate switchers). Estimation results will represent the within group elasticity. I examine the elasticity between customer groups to identify the customers who are most likely to respond to an increase in price. I hypothesize that the customers who face a sudden higher demand charge due to higher peak demand incur an elasticity that is higher than customers who have always been in the same rate schedule. Customers who switch rate schedules could be more sensitive to price for two reasons. First, they tend to be close to the rate switching threshold (see table 1.2 for details). Customers who have mean monthly peak demands close to either threshold are subject to switching rates and facing a higher peak demand. Hence, it is beneficial for these customers to manage their peak demand to be lower than the threshold. Second, customers who switch rates face a higher demand charge. As indicated in table 1.2, customers who switch rates to either J or P face a higher total bill compared to before the rate switch.

The coefficient on D_{pit} (β_p) are interpreted as the impact of one more day with a mean temperature falling into bin p on y_{itk}. Equation (1) is estimated separately for each rate group, k. Rate group summary statistics are presented in table 1.2. The coefficient of interest is β_1 and β_2, which estimate the price elasticity of demand for customers in rate group k and of those in category k with PV.

To add variation to this analysis, I also employ a difference and differences (DID) method. Samples (1) and (2) are also utilized for this equation (see section 3 on sample explanation). This analysis will allow us to look at the treatment effect of switching rates with customers who have never experienced a switch as the control group. Unlike equation (1), this regression focuses on the average treatment effect of switching rates. Hence, the elasticity obtained from the regression will show the elasticity after switching compared to a control group.

The equation is as follows:

$$y_{itk} = \beta_1 * ln(p_{t-1,k}) + \beta_2 Switch_r + \beta_3 * ln(p_{t-1,k}) * Switch_r + \beta_4 * ln(p_{t-1,k}) * PV_{itk} + \beta_5 * PV_{itk}$$
$$+\beta_p * D_{itpk} + \alpha_y + \mu_m + \eta_i + \epsilon_{itk} \tag{1.2}$$

where equation (2) is similar in set up as equation (1) except for the variables $Switch_r$ and $ln(p_{t-1}) * Switch_r$. The inclusion of these variables allows for equation (2) to follow a DID set up that examines the average treatment effect of an event (switching rates). The variable $Switch_r$ is the treatment and also the time dummy under the DID environment. This is because this variable represents unity at the time the customer switch rates and also an indicator of whether the customer is a rate switcher. The variable $ln(p_{t-1}) * Switch_r$ is the interaction of the rate switching variable and the price variable, and the coefficient will provide the price elasticity of demand for customers who switched rates relative to the control group, who are those that have always been in the same rate schedule. The subscript k is a group indicator that represents the rate category. Specifically, the rate category include four groups. These groups are customers who are "always G", "always J", "alwaysP", and "rate switchers." Rate switchers are the treatment group. However, equation (2) is run separately for large C&I and small C&I customers. The large C&I sample includes customers who are "always J", "always P", and customers who switched to rate P. The small C&I sample includes customers who are "always G", "always J", and customers who switched to J. The customers who are always in rate J are included in both samples, as indicated in the data section.
It is important to note that these equations do not control for endogeneity, but this issue will be addressed in the next section.

1.4.2 Grandfathering

Switching schedules is endogenous because the customer itself makes the decision to increase or decrease their peak demand based on factors including electricity prices and business operations. Business operations and equipment utilized at the customer site are not observed in the billing data. To address this issue, I utilize a sample of customers that have been "grandfathered" as a control group and calculate the price elasticity of demand.

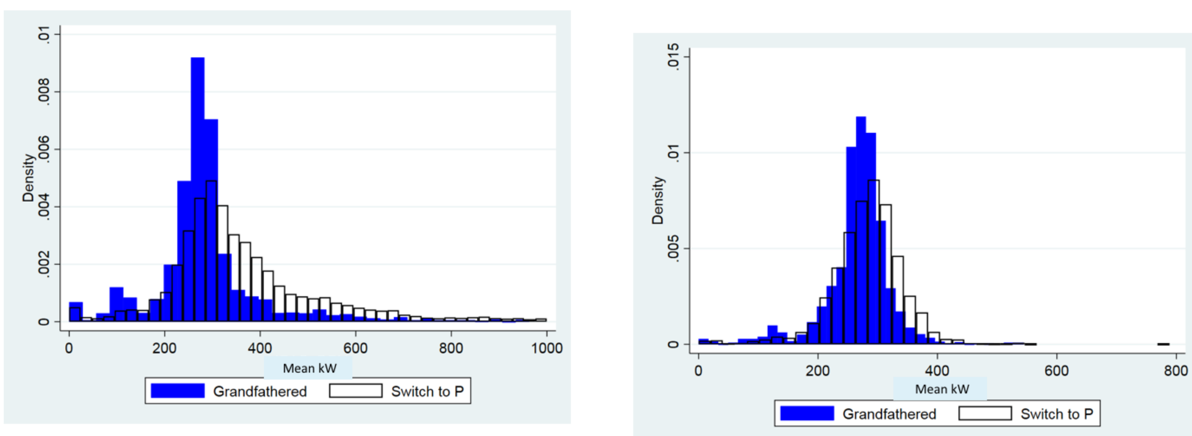
As stated in the introduction, there are customers in the sample that have been "grandfathered." These customers are exempt from the rules that govern rate placement. In other words, grandfathered customers do not switch to rate schedule P regardless of consuming passed the 300 kilowatt threshold three times in a given year. Figure 1.4 shows the relationship between average monthly kilowatt hour and kilowatt for J and P customers, with red indicators representing the observations for P customers and blue for J. It can be seen from the figure that blue and red observations collide with each other, when this should not be the case if the rules governing the rate placement are true. If the rate placement rules hold, the two colors should be separated around the cutoff at 300 kW because that is where rate switching occurs. Hence, figure 1.4 shows that there are customers who should be placed in rate schedule P based on their monthly peak, but are categorized as rate J customers and do not face a higher demand charge. This is due to a change in rate category policy at HECO. Rate schedule J became closed to new customers with kW demand equal to or greater then 300 kW after June 2008, and existing J customers who had maximum demand measured kW demand equal to, or greater than 300 kW were allowed to continue receiving service under rate J. Hence, new customers who tied a contract with HECO and had kW demand equal to or greater than 300 kW were placed under rate schedule P, while existing J customers with kW demand measurements over 300 kW were grandfathered from this rule. Moreover, it could be argued that customers who have a large kWh usage to choose to be under rate P because of the lower volumetric charge. However, the green line in figure 1.4 (a) shows that this is not the case. Customers would need to have a mean monthly kWh and kW combination above the green line given their volumetric and demand charge to have an incentive to switch to rate P. Thus, we can say that there is no incentive for customers to want to be placed in a rate schedule with a higher demand charge and lower volumetric charge, and these types of customers do not exist in this sample. We use the DID method to estimate the effect of rate changes using grandfathered customers as a control group. The equation is as follows:

$$y_{it} = \beta_1 * ln(p_{t-1}) + \beta_2 Switch_p + \beta_3 * ln(p_{t-1}) * Switch_p + \beta_4 * ln(p_{t-1}) * PV_{it} + \beta_5 * PV_{it}$$
$$+\beta_p * D_{itp} + \alpha_y + \mu_m + \eta_i + \epsilon_{it} \tag{1.3}$$

The above equation is the same as the DID set up in equation (1.2), but the regression is applied to a different sample. The sample consists of grandfathered establishments and customers who have experienced a rate switch at least once. Moreover, to assure that the control group and the treatment group have similar pre-consumption trends, the sample is further narrowed by deleting establishments that are outside of the common support. A histogram of peak demand is illustrated in figure 1.3. The common support is peak demand between 100 kilowatts and 600 kilowatts. Establishments who have mean peak demand outside of this range are deleted from the sample. After restricting the sample there are 12,573 observations for this analysis. The standard errors are clustered using two way clustering that incorporates the customer identification number and time period (year-month).

Grandfathered customers serve as a control group in the analysis to address the endogeneity issue that arises because customer rate placement is not random. Ito (2014) addresses this issue by segmenting the treatment and control group by the territory boarder between two power providers. Territory boarders lie within city limits, and households in the same city can be served by different utilities. Hence, rate placement is exogenous and price variation comes from the relative price of the two power providers. However, customers in our sample are serviced by a single utility and price is dependent on a customer's peak demand. To address this issue, we create a control group that consists of customers who are exempt from the rules of rate placement (grandfathered customers). The treatment group in our analysis consists of customers who have switched rates to rate schedule P and are not grandfathered. Table 1.4 presents the mean monthly kilowatt and kilowatt hour usage for the treatment and control groups. It is important to note that the grandfathered variable is a time variant variable that is equal to unity when the customer exceeded the 300 kW threshold three times within a 12 month period (as per the rate switching rules), but did not switch rates to a schedule with a higher demand charge. In addition, the "switch to P" variable in table 1.4 is also a time variant variable and is equal to unity when the customer switched rates to a rate schedule with a higher demand charge after exceeding the 300 kW threshold three times with 12 consecutive months. As seen from the table, grandfathered customers and rate switchers have almost similar monthly kWh but different monthly bills. Grandfathered customers have monthly bills that are about $5,100 less than customers who have switched rates even though grandfathered customers have greater peak demand. This is because grandfathered customers face the same fixed rates and demand charges of those in rate schedule J regardless of having mean peak demands that are high enough to be in schedule P. To put the grandfathering concept into perspective, table 1.4 also includes what the bill for grandfathered customers would be if they faced rate schedule P rates. In other words, we utilize their monthly kWh and peak demand data to calculate an alternative bill. The last row in table 1.4 shows the results. Grandfathered customers face a mean monthly bill of around $52,600 when faced with schedule P rates. This value is higher than the mean bill that the treatment group (Switch to P in table) faces, which is $51,900. Thus, grandfathered customers indeed have either higher monthly kWh or peak demand than rate switchers but do not face the consequence if a higher peak demand. The elasticity estimates are compared between rate switchers (treatment) and grandfathered (control group) customers. Ideally, grandfathered customers should have low elasticity due to the fact that they are not exposed to the risk of being bumped up to a rate schedule with higher demand charge regardless of their monthly peak demand.

Figure 1.3: Before and After Common Support Restriction on Sample

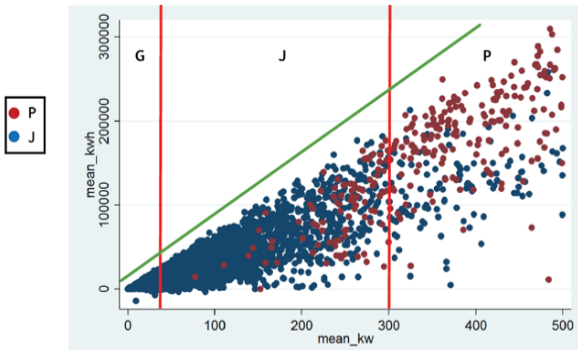


(a) Histogram without common support restriction

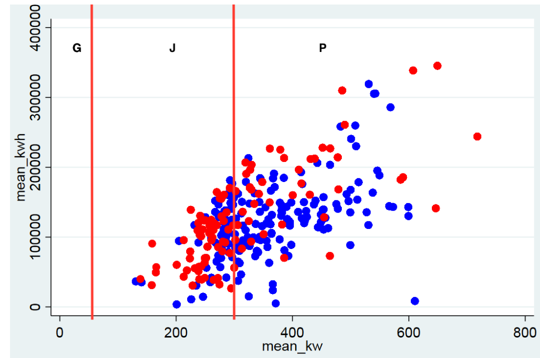
(b) Histogram with common support restriction

Note: Figure (a) The above histogram shows the frequency of average monthly peak demand per customer. The sample is restricted to those who have experienced a switch to rate schedule P and grandfathered customers. Figure (b) This histogram illustrates the distribution of monthly mean kW changes when restricting the sample further based on the common support of figure (a).

Figure 1.4: Entire Sample versus Grandfathered and Switchers Sample



(a) Scatter with all J and P rate customers in sample



(b) Scatter with common support restriction on grandfathered and rate switchers with fitted line

Note: Figure (a) The above scatter plot shows the relationship between monthly mean kW and kWh for a restricted sample of rate J and P customers only. The green line indicates the threshold that the kW and kWh combination where being in a lower rate schedule benefits the customer in terms of billing. Red lines indicate the "switching" thresholds, 25 kW and 300 kW, respectively. Figure (b) This scatter plot restricts the sample to rate switchers to P and grandfathered customers only. The red and blue dots apply to the rate switchers and grandfathered customers, respectively. The red horizontal line indicates the switching threshold.

Table 1.4: Monthly Usage for Grandfathered and Rate Switchers (2012-2017)

	Consumption (000s kWh)		Peak Load (kW)		Bill($)		
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	# firms
Before Grandfathered	111.1	82.7	358.8	747.4	32,205.9	28,438.5	240
Grandfathered	164.5.2	172.3	589.1	1193.02	45,458	51,970.0	240
Before switch to P	104.7	82.0	282.9	144.8	29,110.7	22,914.4	156
Swtich to P	213.6	144.5	472.5	261.1	51,936	33,898.9	156
Grandfathered bills using schedule P rates	.	.	.	.	52,658.83	63,520.7	240

Note: The table above presents monthly mean kWh, kW, and bill for grandfathered (control group) and customers who switched to rate P (treatment group). Standard deviation and number of firms are also presented. Grandfathered customers are defined as those who pass the 300 kW threshold more than three time within a given month but are categorized as rate J. "Before grandfathered" represents the pre- period in which grandfathering occurred. "Switch to P" is a dummy variable that equals to 1 for all the months after the customer experiences a rate switch to P.

1.5 Estimation Results

In this section the results of equation (1.1) and (1.2) with usage and peak load as dependent variables are reported. The subsection starts with the baseline estimation results from equations (1.1). Subsection 2 reports the DID estimation results from equation (1.2). Subsection 3 introduces the effect of PV installation on peak demand. The Results presented in this section do not address the endogeneity issue but will be addressed in later sections.

1.5.1 Baseline Results

We use the fixed effects regression to identify the impact of customer rate switching on electricity usage and peak load. Table 1.5 illustrates the results of the baseline regression for each rate category for small C&I sectors (customers in rates G and J). Each column shows the elasticity estimation results for alwaysJ, alwaysG, and switchers with the log of kilowatt-hour as the dependent variable. It is important to note that this is a baseline regression and does not control for endogeneity using grandfathered customers. The estimates show that customers who have switched to rate schedule J, have a price elasticity of demand of about -0.349 and is significant. This aligns with previous literature that shows elasticity estimates between -0.1 and -0.35 (column 3). The coefficient on lag price for customers who have never switched rates from rate G are insignificant, which can be the case because these customers have never faced a demand charge and face relatively low variation in volumetric rates compared to customers who have experienced rate changes. The price elasticity for customers who have never switched rates and have always been in rate J is -0.133 and significant. This indicates that when comparing within group elasticities between alwaysJ, alwaysG, and switchers, customers who face a jump in rate schedules (and face a higher demand charge) indeed react more to price relative to those who have never experienced such switching behavior.

Moreover, the coefficient on the interaction between price and the PV dummy variable represents the price elasticity of demand for a customer who has a PV system installed. Column (2) in Table 1.5 shows that customers who have always been in rate schedule J and have a PV system installed has a price elasticity of demand of about -0.434 and is significant. The results provide evidence that customers who have installed PV are more responsive to price than before they installed PV. This is because PV customers have less monthly peak demand and energy usage (kWh) after the installation. The reason for this behavior is due to increased awareness and sensitivity to the customer bill as bills drop down to almost zero after PV installation.

Table 1.6 presents the baseline elasticity estimation for customers categorized as alwaysJ, alwaysP, and customers who switched to P. Customers who switched to rate schedule P has a price elasticity of demand of -0.397 and is significant. This value is higher than that of customers who have never switched rates and have always been in rate J, who have an elasticity of -0.158. This indicates that customers who experience a switch to a rate schedule are more price responsive than those who have never switched rates. Comparing "switch" coefficients between tables 5 and 6, it is observed that elasticity estimates for large customers is larger than that of small customers indicating that large customers are more responsive to price. This could be the case because large customers who have experienced a switch to rate P have significantly large peak demand and usage than those who have switched to J (see table 1.2 for details). Hence, it could be that large C&I customers can have a larger share of electricity prices of their total business expenditures compared to small businesses. This is consistent with the paper by Jang, Eom, Kim, & Rho (2015) who shows that C&I customers who have a large share of electricity expenditure are more responsive to dynamic pricing schemes such as critical peak pricing.

Customers who have PV systems and have always been in rate category J (column 1) have an elasticity of about -0.165 and is significant. This evidence shows that customers who have PV systems are more responsive to price changes, which is consistent with the elasticity estimates for small C&I customers who have PV as mentioned above.

Table 1.5: Baseline Regression for Small C&I Customers in Rates G or J

Log kWh	(1) AlwaysG	(2) AlwaysJ	(3) Switchers
Lagprice	-0.064***	-0.141***	-0.32***
	(-4.91)	(-11.55)	(-3.39)
Price*PV	-0.401***	-0.293***	-0.31
	(-3.99)	(-4.80)	(-0.89)
Constant	5.97***	9.18***	7.74***
	(367.22)	(479.76)	(61.44)
Observations	1135474	395964	22116

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table above presents the elasticity regression for small C&I customers. This analysis does not control for endogeneity. The sample used in this table consists of customers categorized under rates G and J. The sample period is 2012 to 2017. Billing data are obtained from HECO.

Table 1.6: Baseline Regression for Large C&I Customers in Rates J or P

Log kWh	(1) AlwaysP	(2) Switchers
Lagprice	-0.014	-0.397**
	(-0.42)	(-2.24)
Price*PV	-0.292***	-0.242
	(-3.15)	(-0.80)
Constant	12.53***	7.649***
	(255.36)	(27.56)
Observations	19219	4737

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table above presents the elasticity regression for large C&I customers. This analysis does not control for endogeneity. The sample used in this table consists of customers categorized under rates J and P. The sample period is 2012 to 2017. Billing data are obtained from HECO

1.5.2 Baseline Results (DID Estimation)

This section reports the estimation results from equation (1.2). This analysis shows the average treatment effect if a customer has experienced a rate change. Tables 1.7 and 1.8 illustrate the estimation results for small C&I customers and large C&I customers, respectively. Table 1.7 shows that the average treatment effect on log kWh of customers who switch to rate J is about -0.161 and is significant. Moreover, the coefficient on price and the rate switching dummy show that the elasticity of customers who switch rates is about -0.3 and is significant. This result is very similar in value with column (3) in table 1.5, which is reassuring. Table 1.8 presents the DID estimation for large C&I customers. The elasticity of customers who have experienced a rate switch is about -0.332, and is close to the coefficient presented in table 1.6, which shows an elasticity of about -0.39. Customers who experience a switch from rate J to P seem to be more responsive than customers who have switched from G to J. This could be explained by the fact that customers who switch to P incur a significant increase in demand charge relative to customers who switch rates from a non-demand charge rate schedule to rate J.

Table 1.7: DID Regression for G and J Customers

	Log kWh
LagPrice	-0.141***
	(-10.40)
Price*PV	-0.104*
	(-1.17)
PV	-0.789***
	(-6.05)
SwitchtoJ	-0.161*
	(-1.74)
Price*Switch to J	-0.302***
	(-4.86)
Observations	1507686

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table above presents the elasticity regression for large C&I customers using a DID approach. This analysis does not control for endogeneity. The sample used in this table consists of customers categorized under rates J and P. The sample period is 2012 to 2017. Billing data are obtained from HECO.

Table 1.8: DID Regression for J and P Customers

	Log kWh
LagPrice	-0.140***
	(-10.51)
Price*PV	-0.316*
	(-5.36)
PV	-0.6723***
	(-8.12)
SwitchtoP	-0.094
	(-0.86)
Price*Switch to P	-0.192 ***
	(-2.51)
Observations	456375

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table above presents the elasticity regression for large C&I customers using a DID approach. This analysis does not control for endogeneity. The sample used in this table consists of customers categorized under rates J and P. The sample period is 2012 to 2017. Billing data are obtained from HECO.

1.5.3 PV and Energy Consumption

This subsection investigates the effect of PV capacity on reducing customer monthly peak demand, and the effect of rate switching on peak demand changes. We hypothesize that a rate switch will most likely increase peak demand because rate schedule placement rules require that a customer have a spike in peak demand within a 12 month period to switch rates. However, the effect of rate switching on monthly kWh is unknown because the rate schedule with highest demand charge face a lower price per kWh consumed. This is because customers in higher rate schedules purchase in "bulk", hence the lower volumetric charge. Therefore, customers who switch rates could consumer more per kWh because they now face a lower volumetric charge. Moreover, the effect of PV capacity on reducing peak demand is examined to investigate the effectiveness of PV in reducing peak demand. As the equation below indicates, we interact kilowatt capacity with the dummy variable for installation of PV.

To investigate how switching rates affects peak demand, we estimate a modified version of equation 1.1:

$$y_{it} = \beta_1 * switch_b + \beta_2 * capacity_{it} * PV_{it} + \beta_3 * ln(p_{t-1}) + \beta_p * D_{itp} + \alpha_y + \mu_m + \eta_i + \epsilon_{it} \quad (1.4)$$

where y_{it} is equal to the dependent variables in question: log kW, log kWh and kW for customer i in time t. The $switch_b$ variable is a rate switching dummy where the subscript b is equal to rates J or P, and indicates which schedule the establishment switched to. This equation adds a new variable, $capacity * PV_{it}$, which is an interaction between the PV dummy and the solar system capacity (kW) for customer i. The PV dummy is a time variant variable that is equal to unity after the date that the customer installs a PV system. The coefficient on this variable will indicate how a one kW increase in PV system capacity will affect peak demand. Finally, the fixed effects and weather variables are the same as equation 1.1.

Table 1.9 shows the results for the estimation of switching rates on peak demand (kilowatt) and log usage (kWh). In regards to table 1.9 column 1 and 3, it is important to note that the coefficient on switching to J is positive because rate switching only occurs when a customer increases their monthly peak demand. The interaction between PV installation and PV capacity is negative and significant for culumns 1 and 3, with a one kilowatt capacity increase leads to about a 0.1 percent decrease in log kilowatt hour. This indicates that peak consumption tends to decrease after PV installation. These results are not conclusive on what time of the day the consumer reduces their peak demand. Instead the results show that monthly peak demand decreases with PV installation. Column (2) in table 1.9 shows the effect of switching rates to J on monthly kWh but is insignificant. Hence, we can't determine whether a rate switch changes kWh consumption.

Table 1.10 illustrates how peak demand changes as a customer changes rate schedules when customers switch from rate schedule J to P. As per table 1.9, the effect of switching on kilowatt hour is unknown since the coefficient is insignificant. However, align with the results from table 1.9, the coefficient on the interaction variable is significant. A one kilowatt increase in PV capacity leads to about a 1 percent and 0.1 percent decrease in log kilowatt hour and log kilowatts, respectively.

Table 1.9: Peak Demand & Usage Regressions for Rate G & J Sample

	(1) kW	(2) log kWh	(3) log kW
Switch to J	9.50	0.056	0.415**
	(1.05)	(0.25)	(2.36)
PV*capacity	-0.107**	-0.0099	-0.00137**
	(-2.80)	(-0.75)	(-2.67)
logprice	-6.282	-0.251	-0.0797
	(-1.60)	(-1.93)	(-0.95)
Observations	13376	18368	13367

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table above presents the effect of switching rates on monthly peak demand (kW) and monthly consumption (kWh). The sample used in this regression consists of customers who are categorized as rates G and J. This analysis does not control for endogeneity. "Switch to J" is a dummy variable that is equal to 1 for all the months after the customer faces a new rate schedule. The sample period is 2012 to 2017. Billing data are obtained from HECO.

Table 1.10: Peak Demand & Usage Regressions for Rate J & P Sample

	(1) kW	(2) log kWh	(3) log kW
Switch to P	111.5	0.173	0.219
	(1.35)	(0.67)	(1.54)
PV*capacity	-0.136***	-0.0107***	-0.00193***
	(-3.64)	(-8.29)	(-3.95)
logprice	-1.93	-0.331***	0.0034
	(-0.73)	(-3.23)	(0.09)
Observations	16179	14553	16179

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table above presents the effect of switching rates on monthly peak demand (kW) and monthly consumption (kWh). The sample used in this regression consists of customers who are categorized as rates J and P.This analysis does not control for endogeneity. "Switch to P" is a dummy variable that is equal to 1 for all the months after the customer faces a new rate schedule. The sample period is 2012 to 2017. Billing data are obtained from HECO.

1.5.4 Results for Grandfather Estimation

Table 1.11 presents elasticity estimates for grandfathered customers when using the DID method. Elasticity is larger for rate switchers then grandfathered customers with a price elasticity of demand of about -0.40. This provides evidence that grandfathered customers indeed are less price responsive when compared to the treatment group. This is the case because grandfathered customers always face the demand charge that is specific to customers in rate schedule J. Specifically, they are not susceptible to rate switching, hence, will never be penalized for having peak demand above the 300 kilowatt threshold. The elasticity estimate of -0.40 for rate switchers align with results presented inn table 1.6 column 2 (which shows an elasticity estimate of customers who switched to P of about -0.39). This section on grandfathering further implies that rate switchers are more price response even after controlling for endogeneity.

Table 1.11: Elasticity Regression: Grandfathered and Switchers Sample

	Log kWh
LagPrice	-0.063
	(-0.68)
Price*PV	-0.08
	(-1.23)
PV	0.024
	(-0.44)
SwitchtoP	-0.352***
	(-2.87)
Price*Switch to P	-0.341***
	(-4.53)
Constant	11.25***
	(67.25)
Observations	19714

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table above presents the elasticity regression for the sample of grandfathers and customers who have experienced a rate switch to rate P. This analysis controls for endogeneity. "Switch to P" is a dummy variable that is equal to 1 for all the months after the customer faces a new rate schedule. The sample period is 2012 to 2017. Billing data are obtained from HECO

1.6 Conclusion

Energy demand has been more difficult to model due to increased deployment of DER. Understanding the nature of consumer demand has become more important for policy makers and the utility to plan future capacity requirements, deploy demand response programs, and match energy demand with supply. This paper studies the response to effective rates of a sample of C&I customers on Oahu. our hypothesis is that rate switchers have a higher elasticity than non-switchers. Price variation that arises when customers switch rates to a schedule with higher demand charge is exploited. Using fixed effects regression to estimate the price elasticity of demand of customers who have switched rates, we find that customers in the setting who switch rates exhibit a price elasticity of about -0.35, while customers who have never experienced a rate schedule change have an elasticity of about -0.133. The empirical results support our hypothesis that customers who face higher fixed and demand charges are more responsive to price changes. This is because customers who have experienced a rate switch face the difficulty of being bumped down to a rate with lower demand charge and become more responsive to prices. Another significant finding is that large C&I customers are more responsive to price than small C&I customers. This implies that customers who have a large share of electricity expenditures are more price sensitive, which is consistent with previous papers.

Another caveat of this paper is addressing the endogeneity issue of rate placement using a random sample of "grandfathered" customers who are exempt from the rules that govern rate schedule placement as a control group. Estimation results find evidence that customers who have peak demands over the 300 kilowatt threshold but do not face the risk of facing higher demand and fixed charges are less responsive to price than customers who follow the rate placement rules. In addition, this paper finds that customers who have switched rates have a load factor that is lower than that of customers who have not, indicating that customers who switched rates have more volatile peak demands. Further research needs to be done to improve the grandfather estimations. For example, a propensity score matching method can be utilized to correct for selection on observables between switchers and the grandfathered customers.

This paper fills the gap in the literature by addressing price response to rate schedule changes of C&I customers. Price elasticity of demand for residential customers have been researched extensively when the share of end use electricity is higher for C&I customers than residential. This is important as demand response programs start to grow in popularity, fueled by installation of advanced metering technology.The evidence provided here can serve as a supplement for decision makers who need to identify potential customers for demand response programs. Moreover, this research contributes to the literature by addressing rate change response of not only small C&I customers, but also investigates price elasticity of large customers who have average monthly peak demand of 863 kilowatts. Results will give insight to the price responsiveness of customers who could possibly have the most effect on the system load.

Chapter 2

Weather Fluctuations and Peaks: An Empirical Analysis of the Electricity Demand in Commercial and Industrial Sectors

2.1 Introduction

Forecasts of electricity demand is important for utilities to plan for future capacity generation and investments. The effectiveness of dynamic pricing schemes on reducing peak demand has been extensively researched by scholars, as it is a factor influencing electricity supply planning. Although understanding customer price response during peak hours of the day can provide further insight to consumer demand, prices, population growth, and economic growth are not the only drivers of electricity consumption. Climate change is one important dimension that must be considered when planning for future generation and demand side management. In addition, electricity demand response to climate is essential for sound policy making. As researchers predict an increase in global average temperatures by the end of the current century (Nakicenovic et al., 2000), it is expected that energy demand will increase as people cope to high temperatures, via increased air cooling demand. The concept of climate change has been studied as greenhouse gases are causing temperature and precipitation levels to increase over time (Deschênes & Greenstone, 2011). Taking temperature into consideration when estimating consumer electricity demand becomes crucial, as individual's energy consumption patterns change with the climate. Past studies agree that temperature is a key variable that affects energy demand. For example, papers by Watson and Mjirhia (2005) and Parkpoom and Harrison (2008) agree that weather variables such as wind speed and precipitation are relatively less important than temperature when predicting energy demand.

This paper presents empirical estimates for the effect of climate induced changes such as temperature on electricity demand for the commercial and industrial (C&I) sector in the island of Oahu in Hawaii. In Hawaii, climate change is likely to affect the power system through rises in cooling demand, rather than heating demand. It is important to note that Hawaii has a low deviation in yearly temperatures. The hottest month in Hawaii is August with an average temperature of 80 degrees Fahrenheit. On the other hand, the coldest month is in January at 71 degrees Fahrenheit. There is no variation in temperature throughout the year compared to states like Massachusetts where the average temperature is 36 degrees Fahrenheit in January and 80 degrees Fahrenheit in August. Climate models forecast that there will be higher temperatures and more frequent heat waves in summer and less frequent cold episodes in the winter (Beniston & Stephenson, 2004). Furthermore, forecasts predict that night-time temperatures in Massachusetts will warm relative to day-time temperatures (Hartmann 2013). A case study done in Massachusetts by (Véliz, Kaufmann, Cleveland, & Stoner, 2017) states that this effect is more noticeable in the winter when the night-time minimum temperature in the Northern Hemisphere increases 0.099 degrees Celsius per decade faster than the day-time maximum temperature. What implications does this have on Hawaii where the mean temperature variance is relatively low and no cold winters? If expected climate change increases average temperatures during the summer, energy consumption in Hawaii will rise due to more demand for cooling. Furthermore, if Veliz (2017) is correct, reduction in the diurnal temperature range will change the daily consumption pattern in Hawaii such that summer night-time consumption rises faster than the day-time. Hence, Hawaii's energy usage will increase overall in the summer with night-time consumption rising faster than the day-time. As peak consumption rises in the night time, additional generation capacity is needed to meet supply with demand at all moments in time. Moreover, the effects of climate change can affect customers in the C&I sectors differently as their load profiles differ. This study examines the relationship between energy consumption and temperatures, and can serve as a supplement for regulators when planning long run capacity requirements for the future.

While existing literature reviews the effect of energy production and use on climate, only recently the reverse has been examined (Véliz et al., 2017) and relies on panel estimation of heavily aggregated data. However, coefficient estimates from papers like (Deschênes & Greenstone, 2011) and (Auffhammer & Aroonruengsawat, 2011) offer some of the best evidence we have on the intensive margin due to the incorporation of panel data in their studies. (Deschênes & Greenstone, 2011)examine variation in U.S. state-level annual panel data of residential electricity consumption using flexible functional forms of daily mean temperatures. They find that there is a proportionally larger increase in energy usage on days where the temperature exceeds 90 degrees Fahrenheit. Specifically, the authors find a U-shaped response function where electricity consumption is higher at extreme temperatures. A similar method will be adopted in my paper. The panel data approach will allow me to control for differences in unobservable characteristics across customers in the sample. Moreover, a paper by (Auffhammer & Aroonruengsawat, 2011) simulates how the residential sector's electricity consumption will be affected by different scenarios of climate change using monthly billing data. The author uses flexible temperature response functions by climate zone, and this will also be incorporated in my paper. Auffhammer finds that temperature response depends on the climate zone. His study also stimulates the effect of increased population and prices on energy consumption. While studies on the residential sector have been conducted, commercial and industrial studies seem to lack. In addition, current studies rely on monthly billing or annual data. My study explains time series variation in 15-minute electricity load over a three year period. This will allow for a more in depth examination of how consumers in the C&I sectors respond to intra-day variation in temperatures. (Franco & Sanstad, 2008) explain temperature response by utilizing grid level data in California. His estimates show a non-linear relationship between electricity load and temperature, while my analysis shows that there is a linear relationship between electricity demand and temperatures. This is because Hawaii has low variation in temperatures throughout the year, making it a state where heating degree days are almost non-existent.

The contribution of the paper to the existing literature is two-fold: (1) While previous studies forecast energy consumption of the residential sector, literature on C&I customers is sparse (Auffhammer & Mansur, 2014). Focusing on large C&I customers can contribute greatly to existing literature because the C&I sector contributes to about 70 percent of end-use energy usage in Oahu (EIA 2012). (2) Micro-level analysis is critical, but for most studies customer-level data is not available(Franco & Sanstad, 2008). Moreover, aggregated panel data and time series variation cannot control for unobserved factors also changing over time, and literature using these types of data are least likely to be informative on climate damages (Auffhammer & Mansur, 2014). However, this paper utilizes micro level panel data of energy demand for large C&I customers collected at the 15-minutes interval level obtained through a confidential agreement with Hawaiian Electric Company. The detailed level data used in the paper can address changes in composition of industry that aggregate level data mask. In addition, the panel data will allow for better understanding of how firms from different sectors respond to temperature while utilizing time fixed effects at the consumer level to address omitted variable biases.

In this paper, I conduct a weekend versus weekend analysis along with a within day temperature response by sector. The identification strategy relies on random hourly local variation in temperature, so concerns about omitted variables bias are unlikely to be a limiting factor for the analysis. The short-run temperature effects on energy demand are measured using a climate model that considers not only hourly temperature but also weather variables such as precipitation and humidity.

2.2 Data Sources

As seen from the previous literature, temperature is not the only factor that affects energy demand. Meteorological stations typically record data for numerous meteorological variables. In my analysis, I obtain a set of variables that could be obtained for the entire period of the analysis. To control for all possible factors, I include a set of not only temperature variables but also non-temperature weather variables including: humidity, precipitation, and wind speed.

2.2.1 Commercial and Industrial 15-Minute Interval Consumption Data

Data are obtained from Hawaiian Electric Company under a confidential agreement. This is a fine data set that includes a 15-minute frequency usage in both kilowatt hours (kWh) and kilowatts (kW). The data consists of C&I establishments for 2014 to summer 2017. There are a total of 500 customers included in this data set, and are not representative of all the establishments on the island of Oahu. Industries for these large C&I customers include: hotels, schools, hospitals, department stores, and grocery stores. Small C&I customers that are in the general non-demand (Rate G) rate schedule is not included in this data set. The sample of this data set consists of large customers that have a meter and a dedicated telephone line that collects and stores data on their electrical usage at 15-minute intervals (Wordpress 2010). Customers included in this sample consists of general demand (rate J) and large power service (rate P) rate schedules. It is important to note that customers included in this data have access to their electrical usage through an internet portal. Participation in this service is voluntary, and access to data is possible through contacting a representative. Specifically, customers have data on the peak demand and energy usage trends throughout the year. Access to the data is possible through the portal at any time and this makes it easier for customers to manage demand and energy usage, documenting the impact of energy-efficient investments, and determining the impact of any new equipment or changes in operations. This information is an important aspect for the analysis because customers understand their usage behavior more than other customers who do not have access to this portal.

I classify customers in this data by industrial codes, which is aligned with the North American Industrial Classification System (NAICS). The major sectors in my sample are: hotels, schools, hospitals, department stores, manufacturing and grocery stores. I observe industrial codes for 90 percent of my sample. Table 2.1 presents summary statistics of each customer sector. As seen from the table 2.1, the health sector has the highest average 15 minute peak (1585 kilowatts). General merchandise and grocery stores have average 15 minute peaks of 308.3 and 260 kW, respectively. Table 2.1 only shows the averages of peak demand consumption rather than the specific time the highest peak occurs by customer.

In addition, I overlay average temperature over average demand (kW) and is presented in figures 2.3 through 2.7 in the appendix. The figures are by industrial sector classified by the NAICS codes to show the differences in the relationship between temperature and energy demand by month. Energy demand is averaged by day to construct this 12-panel figure. The figures show that this relationship differs between industrial sector. For example, the educational sector shows that energy consumption during summer months and the holidays are relatively low due to summer vacation and Christmas holiday. The four "humps" in each panel represents the weekly load for the educational sector, with demand being the highest during the weekdays. Hence, per the figure, the educational sector seems as though they are not sensitive to temperature changes. This is because the educational sector could have a operations that do not correlate with the weather. On the other hand, there seems to be the most correlation between temperature and energy demand for hotels. This could be the case because hotel guests use the most air conditioning on days where they experience the highest temperatures. Moreover, hotel guests have no incentive to use energy efficiently as they are not directly paying for the electricity costs.

Table 2.1: Average 15 minute Demand by Sector (2014-2016)

	kW Average	Standard Deviation	Obs (million)
Education	758.5	2225.3	5.7
Hospitals	1585.5	1669.6	1.7
General Merchandise	308.3	323.7	2.1
Hotels	712.1	631.0	3.9
Grocery Stores	260.0	122.3	3.6

Notes: The table displays summary statistics for five C&I sectors that are observed within the MV90 dataset. The number of observations are in millions.

2.2.2 Hourly Weather Variables

Hourly temperature, precipitation humidity and wind speed data from 2014 to 2016 are collected from Iowa State University, Iowa Environment Mesonet (IEM). Temperature data are in Fahrenheit and wind speed measures are in knots. These data sets are included in the data because they are most likely to affect cooling demand. Previous research has found a correlation between these variables and energy demand. For example, (Hernández et al., 2012) finds that a positive correlation between humidity and energy consumption. Likewise, wind speed may decrease the demand for cooling in hot days. Table 2.2 provides a description of the weather variables. I present the mean, standard deviation, minimum and maximum for each weather variable that is used in my analysis. Weather data are in hour units; hence, the linear interpolation method is incorporated to match this data with the 15 minute interval data set. Figures 2.3 through 2.7 in the appendix illustrate temperature trends from 2014 to 2016. Figures 2.8 illustrates the daily temperature average of every 15 minute interval by year. Daily peak tends occur around 15:45 pm with 2015 having the highest peak out of the three years. Figure 2.9 and 10 show the average temperature by season. As illustrated by the figure, Hawaii has the highest temperatures during July, August and September. In addition, the coldest months in Hawaii in December, January and February.

Customers are scattered across various areas in Oahu, where climate variables can vary depending on the region. Customers located near the mountains can experience different weather than customers who are located near the ocean. To address this, I utilize customer addresses to locate them on the map and use the closest weather station. I cross reference the customer address with the customer name to ensure that electric service is indeed provided to the particular business listed in the dataset. Due to confidentiality of the data, I do not reveal the location of the customers in my sample. Ninety percent of the customers in the sample are in the city of Honolulu, and I use the correlating Honolulu Airport station for my analysis. The remaining 10 percent were not included in the sample because of missing address information.

Table 2.2: Climate in Hawaii (2014-2016 sample)

	Mean	Standard Deviation	Min	Max
Air Temperature	77.6	5.1	59	93
Precipitation (mm)	0.053	0.6	0	42.4
Humidity (%)	67.7	12.43	0	100
Wind (knots)	9.39	5.17	0	34.5

Notes: The table displays summary statistics for weather variables that are obtained from the Iowa State University, Iowa Environment Mesonet (IEM). Units are indicated in the parenthesis.

2.3 Identification and Empirical Approach

This section describes three econometric models used to examine the relationship between temperature and energy demand.

2.3.1 Reaction Curves

Several studies show that the relationship between temperature and energy demand is non-linear (Auffhammer & Aroonruengsawat, 2011). Auffhammer uses temperature bins to accurately capture potential important non-linearities of temperature. On the other hand, studies show a V-shaped relationship between temperature and energy use (Amato, Ruth, Kirshen, & Horwitz, 2005). Hence, the use of temperature bins to correctly to capture non-linear relationship between temperature and energy use becomes an important aspect of the analysis. Since this paper uses 15 minute interval energy consumption data, I use linear interpolation between hourly mean temperatures to construct a weather dataset to match the energy consumption data. Per Auffhammer's approach (2011), 10 temperature bins are constructed by using two separate approaches. The first method is sorting temperature distributions into percentiles and splitting them into a total of ten bins for each C&I sector. The second method uses a specific equidistant for sorting. For the equidistant bins approach, we split the mean daily temperature for each household into a set of 3 degree Fahrenheit bins. Bins 1 and 10 are included to estimate the effect of extreme temperatures on electricity consumption. Note here that the definition of "extreme" differs than that of Greenstone and Deschenses (2011) because Hawaii has a mean minimum temperature of 72 degrees Fahrenheit and mean maximum temperature of 84 degrees Fahrenheit while Greenstone and Deschenses incorporates temperatures that vary from below 10 degrees Fahrenheit to above 90 degrees Fahrenheit. Unlike the approach by Auffhammer (2011) who uses monthly billing data, I do not count the number of days that a daily mean temperature falls into a certain bin because I use interpolated climate variables to match the 15-minute interval energy demand. The coefficient on the binned weather variables indicate the affect of belonging to one of the temperature bins on peak demand relative to the midpoint of all bins.

The empirical equation is constructed using the method by Greenstone and Deschenses (2011), which explains variation in state-level annual panel data of residential energy consumption using flexible forms of daily mean temperatures. This equation is a simple log-linear specification commonly employed in aggregate electricity demand and climate change impacts estimation and is also adopted by Auffhammer (2011). However, in this paper, I use commercial and industrial panel data rather than residential panel data, and I don't count the number of days the mean temperature falls into a bin because both the weather and energy consumption data are matched at the 15 minute interval level. The identification strategy comes from random fluctuation in weather to identify climate effects on commercial and industrial energy consumption. An underlying linear relationship was assumed between the dependent variable (log kilowatt) and the climatic independent variables. The model is as follows:

$$\begin{aligned} logkw_{it} &= \beta_p * M_{itp} + \beta_1 * PREC_t + \beta_2 * HUMID_t + \beta_3 * WIND_t + \beta_4 * W_d \\ &+ \beta_5 * M_{itp} * WIND_t + \beta_6 * M_{itp} * \gamma_h + \alpha_y + \delta_m + \eta_d + \gamma_h + \mu_i + \epsilon_{it} \end{aligned} \tag{2.1}$$

where $logkw_{it}$ is the log kilowatt hour for customer i, in time t where t represents the year, month, day, hour, and 15 minute interval. Note that the dataset used in this analysis is a 15 minute interval electricity consumption profile. M_{itp} are the binned weather variables with p indicating the bin number. $HUMID_t$ is humidity at time t, $PREC_t$ is precipitation at time t, and $WIND_t$ is wind speed at time t. W_d is the weekend dummy, which is equal to one if day d is a weekday and zero otherwise . $M_{itp} * WIND_t$ is the interaction between wind and temperature bins. α_y, δ_m, η_d, γ_h represent the year, month-of-year, day-of-month and hour-of-day (a dummy for each hour of each day) fixed effects, respectively. ϵ_{it} denotes the error term. Moreover, to control for contemporaneous shocks that affect electricity consumption common to establishments, I include μ_i, which indicates establishment level fixed effects. Finally, $M_{itp} * \gamma_h$ is an interaction term between the temperature bins and the hour-of-day dummy. This is added because how each customer responds to temperature change could be different depending on the hour of the day. The main coefficient of interest is β_p where it is interpreted as the impact of one temperature increase in bin p on $logkw_{i,t}$. This equation is estimated separately for the five industries as categorized by the NAICS codes, and can vary in parameter across industries. Standard errors are clustered at the individual firm level. The variables of interest are the measures of temperature.

Instead of solely relying on a simple relationship between energy use and temperature I include other weather variables in the analysis such as humidity, wind speed, and precipitation. As per (Hor, Watson, & Majithia, 2005), I use several weather variables because Hor shows that models used to predict energy demand improve with the addition of more weather variables such as wind speed, and precipitation. Past studies have shown that temperature is the most important variable that affects energy demand while the effect of other variables such as humidity, wind speed and precipitation are not as important (Mansur, Mendelsohn, & Morrison, 2005). However, other variables are still included in the estimation because these factors can still affect customer cooling loads (Parkpoom & Harrison, 2008).

2.3.2 Energy Consumption using Cooling Degree Days

Greenstone (2011) not only examines temperature exposure using temperature bins but also runs a separate regression where temperature is modeled using heating degree days (HDD) and cooling

degree days (CDD). Following Greenstone, I incorporate cooling degree days by using a modified version of equation (2.1). Greenstone uses both heating and cooling degree days. However, due to Hawaii's low variation in temperatures, heating degree days are not used for this analysis. The cooling degree threshold (65 F) is obtained from the National Oceanic and Atmospheric Association (NOAA). In addition, a method by (Fikru & Gautier, 2017) is utilized in this paper, where cooling degree minutes are calculated using 5 minute interval data. The same calculation is used in this paper but I calculate cooling degree hours rather than minutes because temperature is only available at the hourly level . The "cooling degree hour" is calculated by using the temperature for the specific hour minus 65 degrees Fahrenheit. Several studies have also found that cooling degree days can capture non-linearities between temperature and energy use better than using actual temperature values (Hor et al., 2005). Although past studies have found that this is the case, it is still useful to include actual temperature measures in the estimation.
I fit the following equation for commercial energy consumption using a version of equation (2.1) and incorporating cooling degree days and is presented below:

$$\begin{aligned} logkw_{it} &= \beta_1 * CDD_t + \beta_2 * PREC_t + \beta_3 * HUMID_t + \beta_4 * WIND_t + \beta_5 * W_d \\ &+ \beta_6 * M_{itp} * WIND_t + \beta_7 * M_{itp} * \gamma_h + \alpha_y + \delta_m + \eta_d + \gamma_h + \mu_i + \epsilon_{it} \end{aligned} \tag{2.2}$$

The only difference between equations 2.1 and 2.2 are the replacement of temperature bins, M_{itp}, with calculated CDD measures, CDD_t.

A marginal temperature analysis is also considered in this paper to examine how customers respond to marginal temperatures. The equation is a variation of equation (2.2), but I replace CDD_t with the actual temperatures.

2.4 Empirical Results

This section is divided into three subsections, the first section presents the empirical results of equation 1. Instead of including a regression table, I illustrate the results of temperature changes on energy demand using reaction functions, and are shown in figure 2.1. The second section explores how extreme temperatures affects energy consumption. Finally, I present the effect of temperature reaction to energy demand on weekends versus weekends.

Reaction Functions

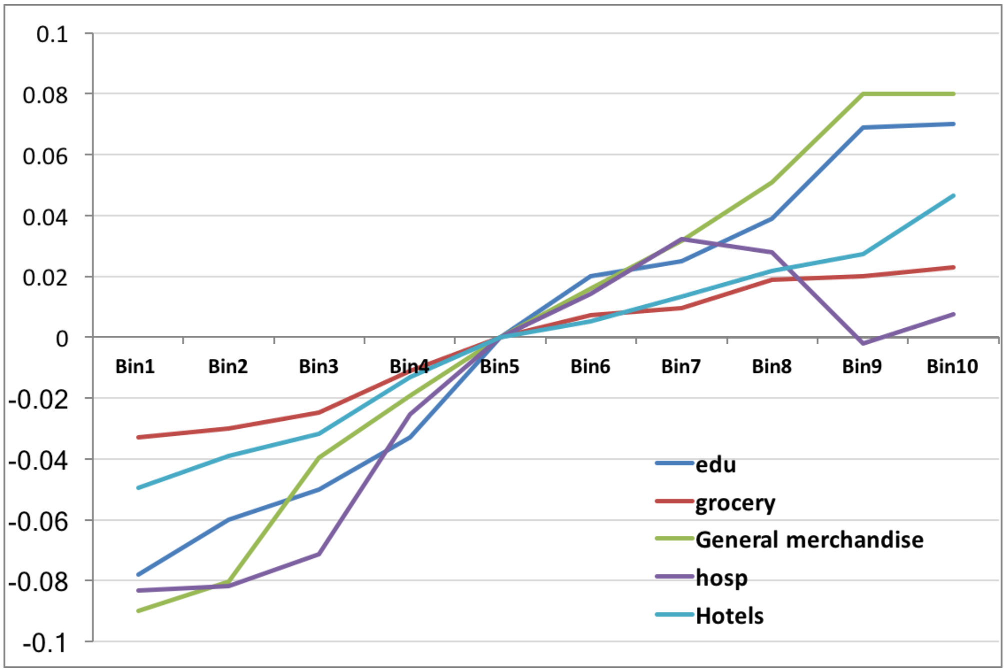
This section explores the effect of temperatures on log kilowatt commercial consumption using the 10 temperature bins defined above. Figure 2.1 plots the estimated reaction function linking log consumption and the ten temperature bins by sector. This figure is created using the method by Auffhammer (2011), who uses temperature bins to exploit the effect of temperature on residential energy consumption. This paper uses a similar method but utilizes commercial data rather than residential data. Each line in figure 2.1 represents a C&I sector. The horizontal axis represents the bins from 1 to 10 and their respective temperature ranges. The vertical axis shows the coefficient on M_{itp}. The base case is bin 5, which has a temperature range of 71-73 F. The coefficients report the impact of being in a specific temperature bin on log peak consumption. Estimates from previous studies show a U-shaped reaction function such as results found from Deschenes and Greenstone (2011). A common assumption inherent in all the linear symmetric models is that there is a shift from heating devices to cooling equipment for infinitesimal deviations from the balance point temperature of 65 Fahrenheit (Fazeli, Ruth, & Davidsdottir, 2016). However, reaction curves in this paper are expected to be upward sloping as Hawaii does not experience a temperature range where consumers require increased heating demand. Figure 2.1 illustrates an increasing function and the shape is similar to that of the right hand side (hottest temperature bins) of the U-shaped reaction functions that Deschenes and Greenstone estimate. Moreover, Auffhammer (2011) has reaction curves for regions in California that indicate an upward sloping or flat reaction curves than a U-shaped one. His curves show regions that are responsive to higher temperatures have a relatively flat curve at lower temperatures but linear and upward sloping from about 70 degrees Fahrenheit and above. This is consistent with the curves in my paper, as sectors are responding more to temperatures that are higher than 70 degrees. However, the magnitude of the response to higher temperature bins are slightly higher than that of Auffhammer. His curves show that the regions who respond the most to temperatures increase their consumption up to about 4 percent at the most. My curves show that sectors who are most responsive increase their consumption about 8 percent at the highest temperature bins. This discrepancy can be explained by the fact that Auffammer utilizes data for residential customers rather than C&I customers and it is simply the case that commercial customers respond differently

.

Figure 2.1 shows that energy demand indeed increases with higher temperatures especially for the education, accommodation, grocery and merchandising sectors. General merchandise and the educational sectors are most responsive to temperature changes. This could be because department stores provide face-to-face services with the customers that are constantly coming in and out, and increased temperatures translates to more cooling demand to accommodate these customers. Moreover, when considering the share of air conditioning as a total of energy consumption, these two sectors most likely have the highest share of air conditioning. For example, grocery have other equipment that use energy such as refrigeration, which decreases the share of air conditioning of the total. However, the medical sector shows an non-linear reaction function, where customers are more responsive to mid-temperatures between bins 6 and 7 rather than extreme temperatures. The medical sector tends to be more responsive at lower temperatures.

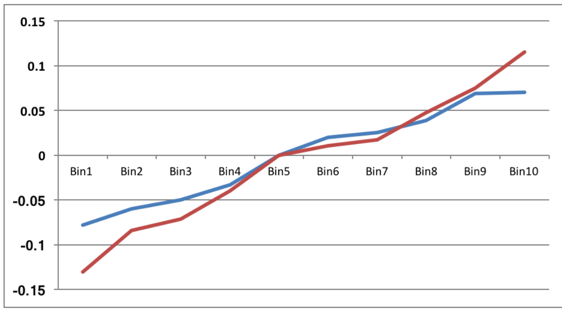
Following the literature, I report response functions by using two methods for bin sorting that are introduced by Auffhammer & Aroonruengsawat (2011). The first option is sorting daily mean temperature experienced by firm i into one of the ten temperature bins using a specific equidistant (3 degree Fahrenheit). The second approach is to split daily mean temperatures into a set of percentiles and using them for sorting. There is no clear guidance on which approach is better. Hence, this paper incorporates both methods. Figure 2.2 plots the estimated temperature response coefficients for each sector against the midpoints of the bins for the percentile and equidistant bin approaches. The red line indicates the percentile approach while the blue line indicates the equidistant approach. These curves are not normalized. Using the percentile approach for bin sorting tends to generate an upward sloping curve for the accommodation sector but overall it is reassuring that the coefficients estimates are similar.

Figure 2.1: Reaction Curves for all C&I sectors

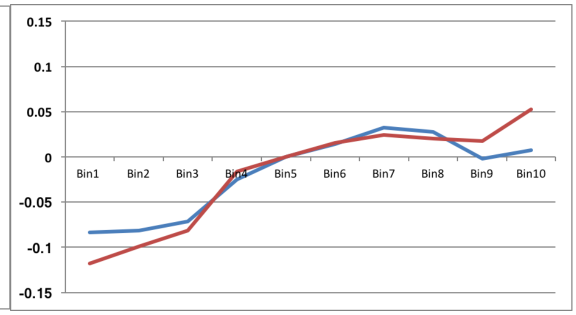


Notes: The figure displays the estimated temperature slope coefficients for each of the ten percentile bins against bin five. This is obtained by fitting equation (1) for log kW in each C&I sector. The lines indicate the reaction curve for a C&I sector. Bins for these reaction curves are sorted using the equidistant approach. See text for more details.

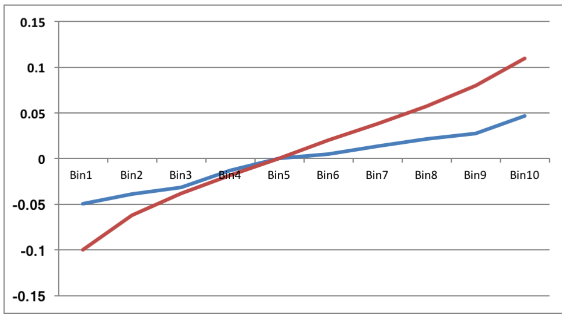
Figure 2.2: Reaction Curve: Equidistant and Percentile Approach Comparison



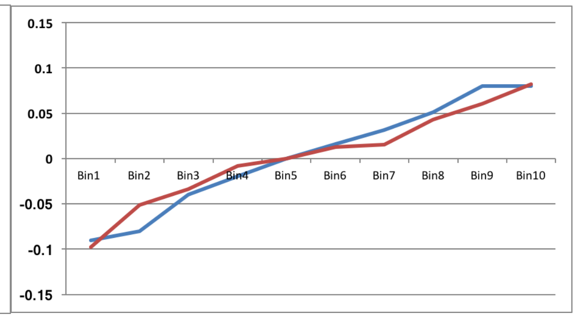
(a) Education



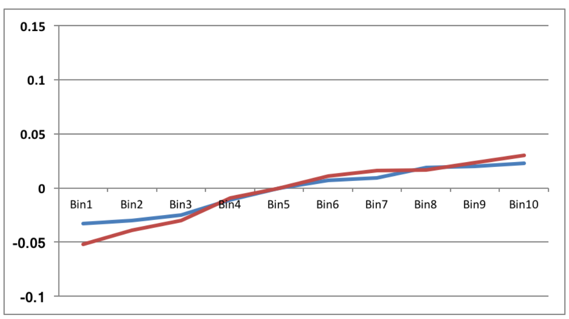
(b) Hospitals



(c) Hotels



(d) General Merchandise



(e) Grocery

Note: Figure (a) through (e) above illustrates the two reaction curve that are made using 2 different approaches for bin sorting: equidistant and percentile. The red line indicates the reaction function under the percentile approach while the blue indicates the curve created under the equidistant method.

Impact of Extreme Temperature on Electricity consumption and Degree Day Approach

This section looks at the relationship between extreme temperature and peak demand. Table 2.3 documents the lowest two (coldest) and highest two (hottest) temperature bins and their estimates. As seen from the table, there is heterogeneity in the estimated effects of temperature on peak demand across sectors. The base bin is set to five, which includes temperatures ranging from 71 to 73 Fahrenheit. Peak demand tends to increase as temperatures become higher, which is consistent with other studies. However, estimates in this paper are higher than that of Greenstone

(2011) and Auffhammer (2011) by 30 percent or more. Both studies find estimates that lie between negative three and positive three percent for all temperature bins. This paper possibly exhibits higher estimates because of a difference in temperature bin construction. Greenstone (2011) and Auffhammer (2011) construct bins by count the number of days the daily mean temperatures lie in a certain bin in each billing cycle. My study does not utilize monthly data and does not require counting days when sorting the bins. The estimates in table 2.3 shows the percentage increase of being in a temperature bin relative to the base bin (bin 5). Estimates that lie within the range of previous studies are the Grocery and medical sectors., but these sectors are among the sectors than are not quite responsive relative to to other sectors. Moreover, the medical sector has coefficients that are positive and insignificant. Consistent with table 2.1, the most responsive sectors are the general merchandise and education and is significant. These sectors seem to be the most responsive to both low and extreme high temperatures, but more responsive to lower temperatures than higher temperatures, with education and medical sectors decreasing their peak consumption by 8 and 9 percent respectively. On the other hand, these two sectors respond to higher temperatures less with an increase in peak consumption of 7 percent when located in bin 10. As mentioned in the previous subsection, the merchandising and educational sector may also be responsive to outside temperature because it has a higher share of air conditioning as a share of total electricity usage relative to other C&I sectors. Thus, energy demand can increase as the temperature rises via increased air conditioning demand. and vise versa. In addition, the merchandise sector can have higher response functions because businesses have to accommodate customers using air conditioning when the temperature increases relative to the other sectors where the inside air conditioning is most likely fixed and is not changed frequently. Finally, the least responsive to temperatures are the hospitals and grocery with insignificant results at higher temperature bins. Hospitals can have a lower share of air conditioning as a total of energy demand because of other high powered machines that are utilized within the facility.

The last column in table 2.3 illustrates estimates from the regression where temperature is modeled using cooling degree days (degree-day approach). This is an approach that is dominant in the literature and incorporated in this paper (Greenstone & Deschenes 2011). The justification of incorporating degree days is based on the idea that hot days should cause greater increases in energy consumption in Hawaii where high temperatures are relatively frequent. Moreover, this approach fills the gap that the "bins" regression fails to fill: evidence that the frequency of hot days is related to the energy consumption responsiveness of hot days. Greenstone reveals tremendous

Table 2.3: Estimates of the Impact of Weather Conditions on Commercial Energy Use

Log kW	Bin1 <61F	Bin2 62-64F	Bin9 83-85F	Bin10 >86F	CDD
Education	-0.078**	-0.061***	0.069***	0.071***	0.022 ***
	(-2.35)	(-4.86)	(3.00)	(2.82)	(5.98)
Hotels	-0.049***	-0.038***	0.027***	0.046***	0.009***
	(-6.83)	(-7.47)	(14.34)	(14.31)	(7.27)
Merchandise	-0.090**	-0.803 ***	0.082***	0.079***	0.011***
	(-2.65)	(-2.96)	(7.60)	(7.36)	(3.83)
Hospitals	-0.083*	-0.081*	-0.001*	0.007	0.004**
	(-2.00)	(-1.96)	(-0.49)	(-0.40)	(2.25)
Grocery	-0.032***	-0.030***	0.019***	0.023***	0.006***
	(-7.01)	(-8.79)	(10.94)	(15.7)	(24.7)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The estimates are from fixed-effects regressions based on a sample of about 6 million observations. The dependent variable is the log of 15-minute kW demand. Control variables include humidity, wind speed, and precipitation. In columns (1)-(4), temperature is modeled with ten temperature bins using the percentile approach (Auffhammer & Aroonruengsawat, 2011). The highest and lowest bins are reported in this table. The final column (5) are from a separate regression that incorporates cooling degree days rather than the temperature bins. CDD are calculated with a base of 65 degree Fahrenheit. Standard errors are clustered at the customer level.

heterogeneity in response functions for residential energy consumption when using a specification that includes degree-days. Greenstone's estimates lie within negative one percent to two percent is consistent with my findings. Based on table 2.3, the range of coefficients in column 5 (CDD estimates) lie within 0.6 to 2.2 percent. The results found in table 2.3 are consistent with the reaction functions in figure 2.1, where merchandising and education sectors are the most responsive while the medical sector is not.

Marginal Temperature Increases and Energy Consumption

In this section, we explore how a marginal temperature increase affects peak demand. Per the primitive variable approach by (Sailor & Muñoz, 1997), temperature was found to be the dominant independent variable, explaining more than 80 percent of the energy consumption. Moreover, plots of monthly electricity consumption versus state-wide temperatures indicate a clear division between summer and winter. Thus, I conduct a fixed effect regression analysis using temperature as the only independent variable. A similar approach is conducted by (Crowley, Joutz, et al., 2003). They relate peak hourly electricity demand directly to hourly weather readings by considering load shape forecasting and creation of detailed one-hour short term forecasts.

My estimates align with Crowley and Joutz (2003), where they run a simulation over a particularly hot month in July using residential data. They find an average demand increase of 3.8 percent over

forecasts using actual temperature data. My estimates are overall lower, but close in value to their study. My approach incorporates equation 2.1 but replaces the bins with 15 minute temperature estimates. Table 2.4 shows again that the education and merchandising sector responds the most to a one increase in temperature at about 1.6 and 1.4 percent, respectively. The hotel sector is the second most responsive to price at a one Fahrenheit increase leading to a 2.5 percent increase in peak demand. This could be the case because guest rooms make up for most of the conditioned area within a hotel and guests have no incentive to conserve energy at high temperatures. Thus, customers can respond to higher temperatures via an increased demand for air conditioning.
Estimates from other sectors align with coefficients estimated previous studies such as Crowley and Joutz (2003), which considers the impact of a 2 degree Fahrenheit increase in the daily temperature on hourly peak loads. Their results show that an average demand increase of 3.8 percent. Since my paper considers a one degree Fahrenheit increase, the approximate increase of a 1 percent increase is about 1.9 percent according to the estimates from Crowley and Joutz. This is consistent with the results in table 4 that indicates a one degree Fahrenheit increase translates to an increase in 0.5 to 2.5 percent increase in demand (excluding the coefficient on merchandise).

Table 2.4: Estimates of Marginal Temperature Increase on Peak Demand

	LogkW
Education	0.016***
	(4.02)
Hotels	0.012**
	(7.27)
Hospitals	0.002
	(0.21)
Grocery	0.001***
	(10.66)
Merchandise	0.014***
	(2.83)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The estimates are from fixed-effects regressions based on a sample of about 6 million observations and 5 industrial sectors. The dependent variable is the log of 15-minute kW demand. Control variables include humidity, wind speed, and precipitation. Temperature exposure is modeled without using temperature bins, but uses temperature and temperature squared to account for non-linearity of the affect of temperature on log kW. The estimates indicate a one degree Fahrenheit increase on log kW, and is reported for each sector separately. Standard errors are clustered at the customer level. See text for details.

Hence, as noted in other studies, there is a strong correlation between energy demand and temperatures. These results signal that responsiveness to temperature depends on two aspects: (1) air conditioning as a total share of energy demand and (2) the volume of customers that an establishment faces. Face-to-face services such as the merchandising sector can be more responsive to temperatures as they have to accommodate customers in a timely manner relative to other sectors. The merchandising sector is the most responsive due to not only the contribution of air conditioning of the total, but also consumer behavior within the business. (Cawthorn, 1998) states that weather has a profound influence on consumer behavior, affecting consumer choice, store traffic volume and demand for certain products such as beverages, beach wear, sporting goods, and lawn and gardening items during hot months. On the other hand, hospitals and grocery sectors can be less responsive to temperatures as total energy demand consists of not only air conditioning but medical machinery, labs, and freezers/refrigerators. An interesting case is the contribution of air conditioning to the total energy demand for the hotel sector. This can be ambiguous due to technology that adjusts room temperatures depending on the presence of a guest and pool heating. This makes it difficult to distinguish whether air conditioning demand is derived from the number of guests or the outside temperature. Thus, the next sector further examines the possible explanations of energy demand response to higher temperatures.

Temperature versus Occupancy on Energy Demand

Hotels can have a large share of air conditioning as a total of energy demand, and demand for air conditioning can change depending on the outside temperature and/or the number of hotel guests. In this section I examine the effect of passenger arrivals to Hawaii on log kWh for the hotels sector along with temperature effects on consumption. It is not clear whether the demand for air conditioning is derived from the occupancy rate or the outside temperature. Hence, the inclusion of daily domestic arrival count is to investigate the magnitude of influence on log kW relative to temperature. I use daily passenger count as a proxy to the hotel occupancy rate since it is only available at a monthly level, when the consumption data is in 15 minute units. The occupancy rate data is obtained from the Hawaiian Tourism Authority (HTA) and includes monthly hotel occupancy rates. Table 2.5 shows the effect of log passenger count on log occupancy rate. The table illustrates that a one percent increase in the log passenger count leads to a 8 percent increase in monthly hotel occupancy rates and is significant. This shows that daily passenger arrivals can be a sufficient proxy for the hotel occupancy rate.

Hence, to better understand the effect of energy demand changes, I include domestic passenger arrival data for the island of Oahu from the Hawaiian Tourism Authority (HTA) as a proxy for hotel occupancy rate in the analysis. The regression equation is as follows:

$$logkw_{it} = \beta_1 * TEMP_t + \beta_2 * \sum_{t=1}^{t-6} LogPassenger + \beta_3 * X_t + \alpha_{yh} + \mu_{hm} + \eta_i + \epsilon_{it} \tag{2.3}$$

where $TEMP_t$ indicates the 15 minute temperature, $\alpha_y m$ is the year-by-month dummy, η_i is the establishment fixed effect, X_t is a covariate of non-temperature variables, and $\sum_{t=1}^{t-5} LogPassenger$ is the sum of the log of daily airport arrivals from period t trhough $t-6$. The sum of daily passenger is included as a right hand variable because the number of passengers that arrive to Hawaii stay for a number of nights. According to the Honolulu Travel Authority (HTA) the average number of nights stayed in Hawaii is about 6. Hence, I use a 5-period lag in the regression. The dataset includes daily number of passengers from 2014 to 2016. The caveat of this data is that it includes arrivals to Honolulu International Airport for both residents and tourists. I estimate the impact of log passenger count on the log occupancy rate. Table 2.5 illustrates the effect of both log passenger count and temperatures on log kW, as well as the effect of the log passenger count on the occupancy rate. The coefficient on temperature represents a one degree increase in temperature on log kW, while the coefficient on log passenger count indicates a one percent increase on log kW.

Table 2.5: Hotel Occupancy Rate and Temperature Sensitivity

	Log Occupancy Rate	LogkW
Log Passenger Count	0.081***	0.030***
	(10.38)	(0.015)
Temperature	.	0.0266***
	.	(0.001)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The estimates are from fixed-effects regressions based on a sample of about 6 million observations and 5 industrial sectors. The dependent variable is the log of 15-minute kW demand. Control variables include the hotel occupancy rate, humidity, wind speed, and precipitation. This table shows the effect of hotel guest occupancy rate on peak demand. Monthly occupancy rates are obtained from Hawaii Tourism Authority. The estimates indicate a one percent increase in guest occupancy on log kW. Bin estimates are pulled from table 2. Standard errors are clustered at the customer level. See text for details.

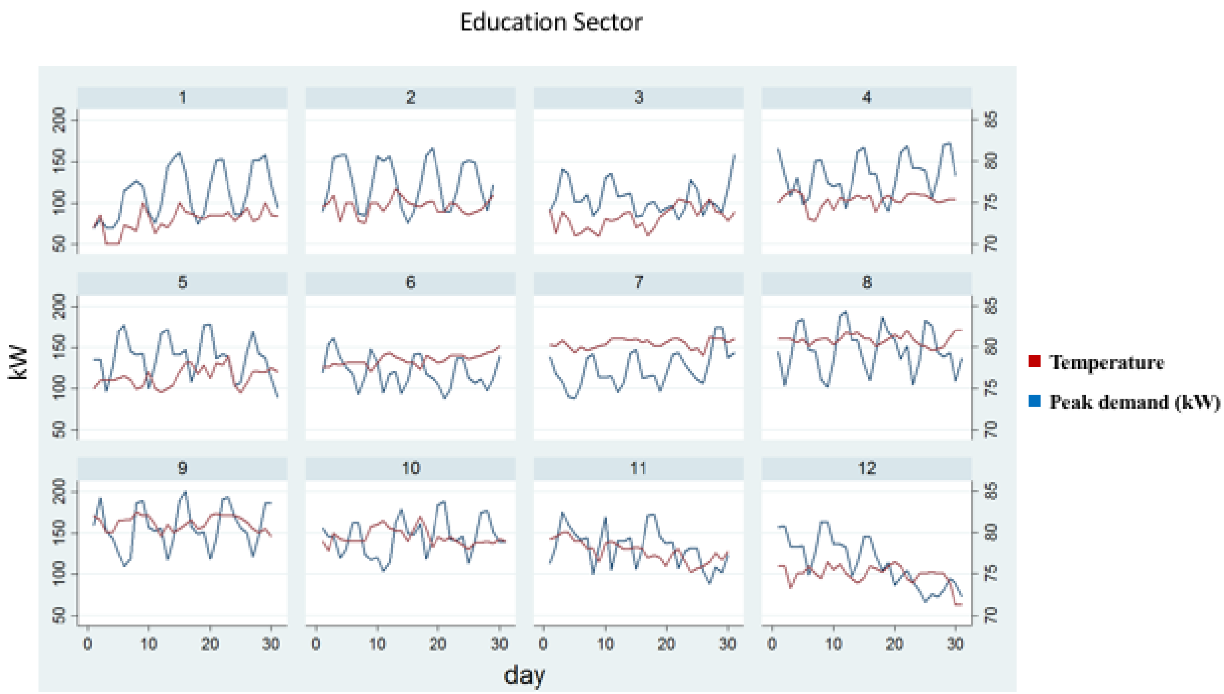
2.5 Conclusion

This paper models that impact of climate change on peak demand for the C&I sectors on the island of Oahu. Although previous studies have shown this relationship for the residential sector, research on the effects of temperature for the C&I sectors have been sparse. Demand data were drawn from a detailed 15-minute panel micro-data under a confidential agreement with Hawaiian Electric Company. A standard set of 15 minute models were estimated accounting for cooling degree temperature effects, climate variables such as humidity, and ownership of solar panels to better understand temperature (including extreme temperature) on peak demand. Hawaii has a unique case because there is little variation in temperatures throughout the year. Hawaii, however, has extremely high temperatures during July, August, and September and this is controlled for in the analysis. Response functions that are generated in this analysis are different from previous studies by Greenstone (2011) and are not "U-shaped" due to the low variance in temperatures in Hawaii. However, the shape of response functions created in this paper are upward sloping and align with the response functions generated by (Auffhammer & Aroonruengsawat, 2011), who shows that residential customers respond most at higher temperature bins. Estimates using cooling degree days align with previous studies who estimate the relationship between extreme temperature and energy consumption, which is reassuring. This study finds that the merchandising sector responds the most to high temperature levels. This is the case when using both the "bins" and cooling degree approach in the regressions. Unlike other sectors, which do not incur complete face to face customer service, the merchandising sector may be responsive to rising temperatures because businesses must accommodate the increase in temperatures via air conditioning. C&I sector that is least responsive to temperatures are the hospitals. Both reaction functions and CDD estimates show insignificant results to higher temperatures. This can be because hospitals do not have a constant flow of customers walking in and out of the establishment relative to the merchandising or grocery sectors.

For future research, as per (Auffhammer & Aroonruengsawat, 2011), variation in temperatures across geographical regions can be incorporated in the analysis. Auffhammer estimates response functions by climate zones in California, which allow for differential effects of days in different temperature bins on a customer's electricity consumption. Temperature variation across regions and over time can provide insight to the impacts of climate change. However, my study has no heterogeneity in geographical placement and most establishments in my sample are in similar regions on the island. The limitation of this study is that the analysis is restricted to one geographical area when there could be more variation in temperatures in Oahu that can be exploited.

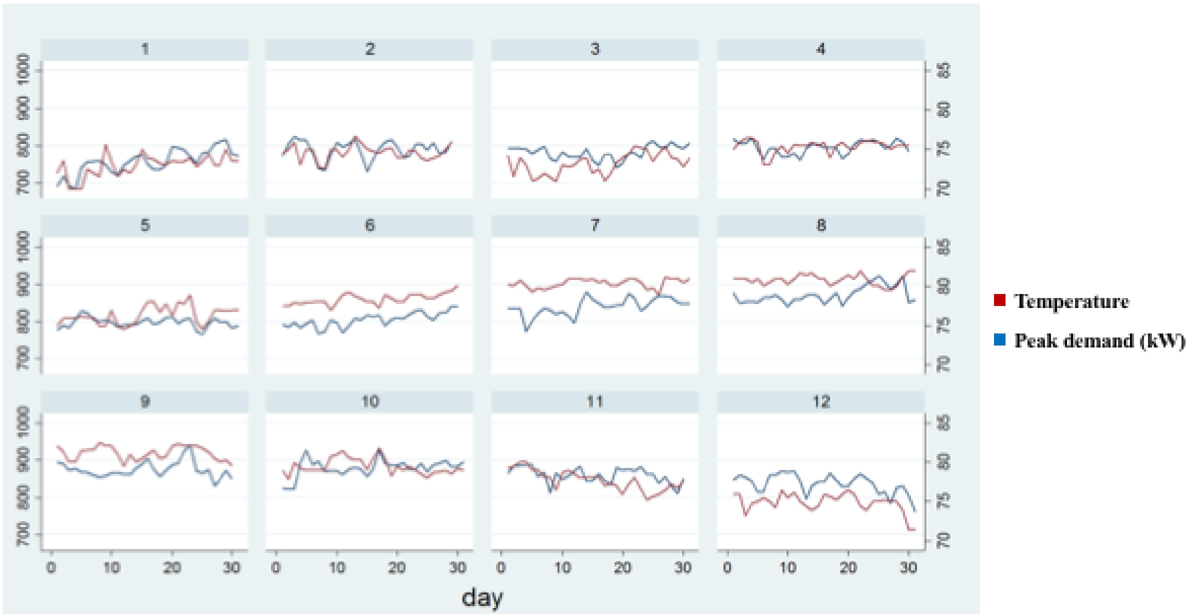
Appendix A

Figure 2.3: Relationship between energy consumption and Temperatures (Education)



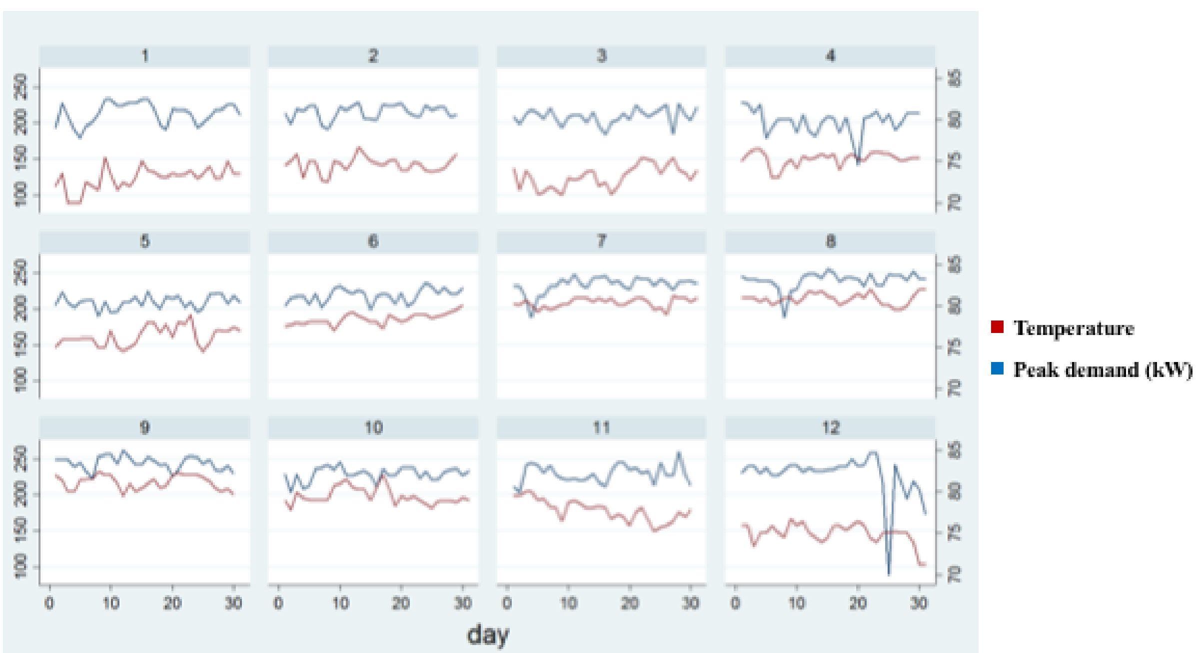
Notes: This figure displays the relationship between temperature and peak demand by month for the education sector 2014-2016 data. The blue line indicates average energy demand per day. In addition, the four "humps" that can be observed in each monthly panel represents the weekly load shape for the particular month. The red line represents the mean daily temperature. See text for more details.

Figure 2.4: Relationship between energy consumption and Temperatures (Hospitals)



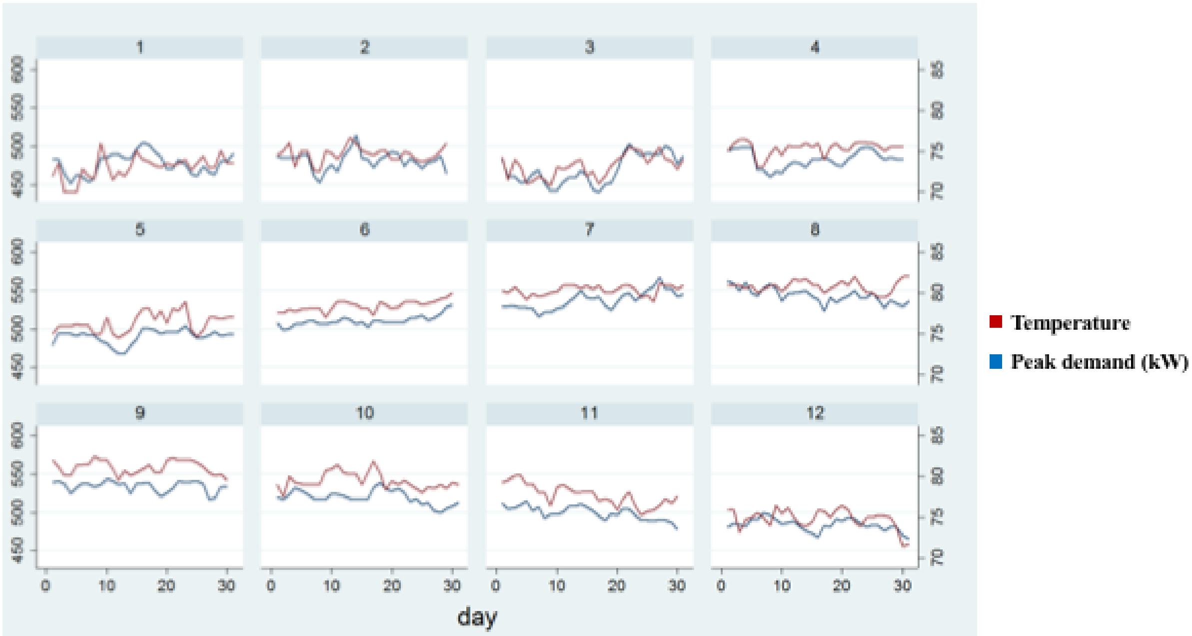
Notes: This figure displays the relationship between temperature and peak demand by month for the medical sector 2014-2016 data. The blue line indicates average energy demand per day. The red line represents the mean daily temperature. See text for more details.

Figure 2.5: Relationship between energy consumption and Temperatures (General Merchandise)



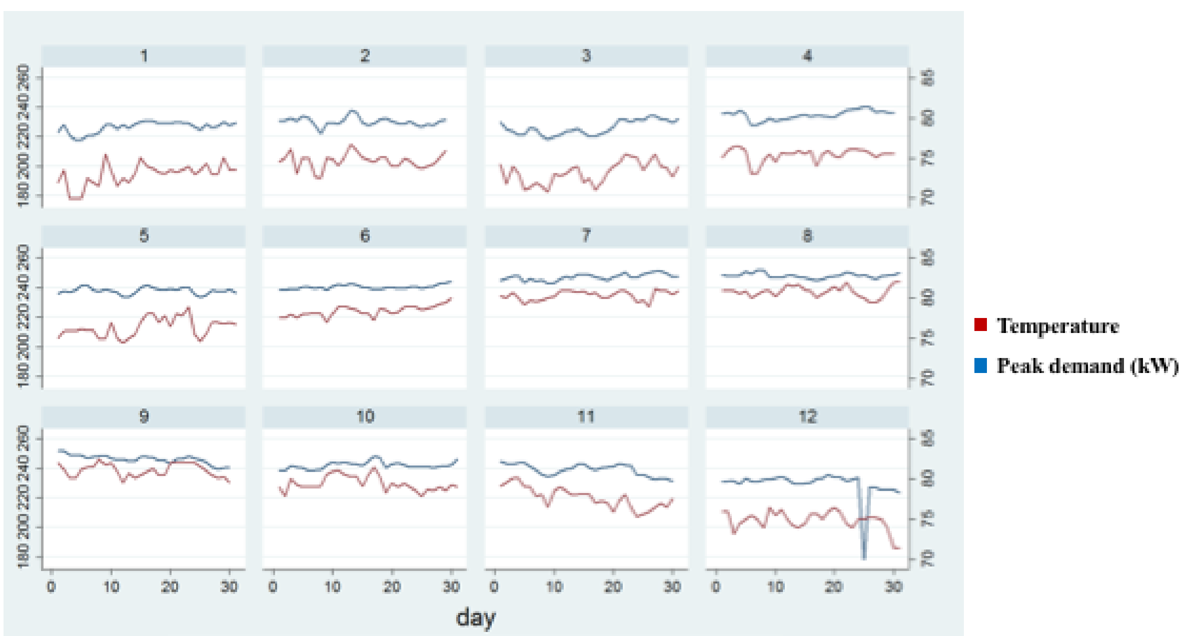
Notes: This figure displays the relationship between temperature and peak demand by month for the merchandising sector 2014-2016 data. The blue line indicates average energy demand per day. In addition, the sudden drop in energy demand in December is the business operation closing due to the holiday. The red line represents the mean daily temperature. See text for more details.

Figure 2.6: Relationship between energy consumption and Temperatures (Hotels)



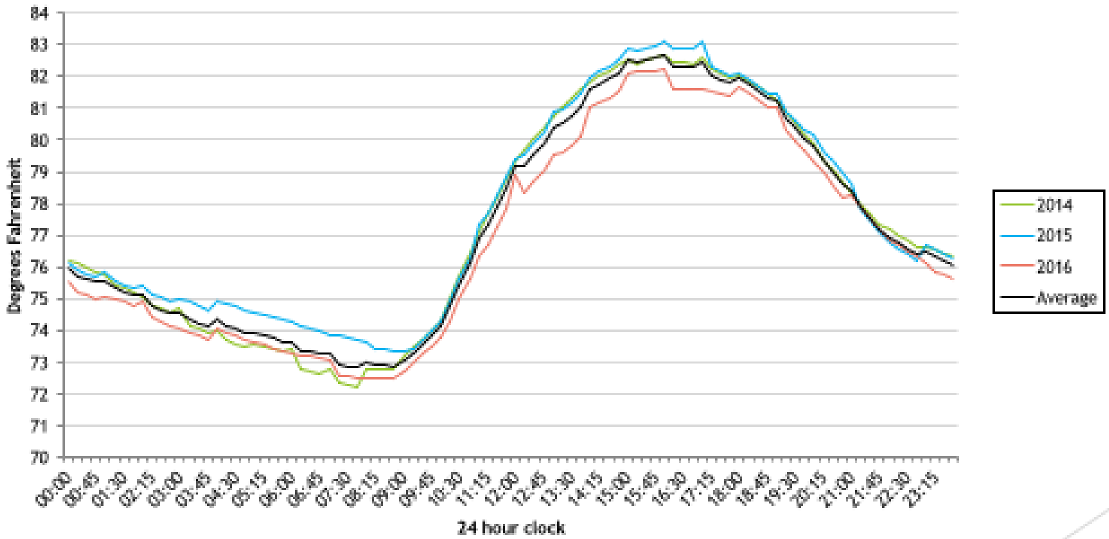
Notes: This figure displays the relationship between temperature and peak demand by month for the education sector using 2014-2016 data. The blue line indicates average energy demand per day. The red line represents the mean daily temperature. See text for more details.

Figure 2.7: Relationship between energy consumption and Temperatures (Grocery)



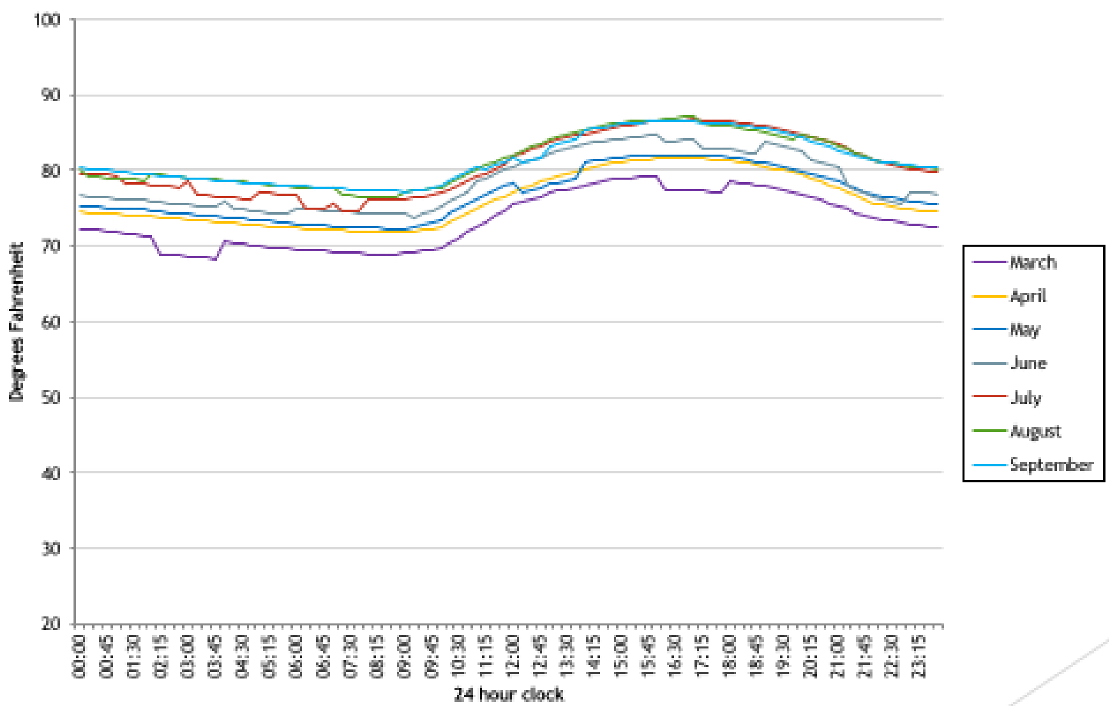
Notes: This figure displays the relationship between temperature and peak demand by month for the education sector 2014-2016 data. The blue line indicates average energy demand per day. In addition, the sudden drop in energy demand (blue line) in December indicates that the business was closed for the holidays. The red line represents the mean daily temperature. See text for more details.

Figure 2.8: Average Temperature by Year



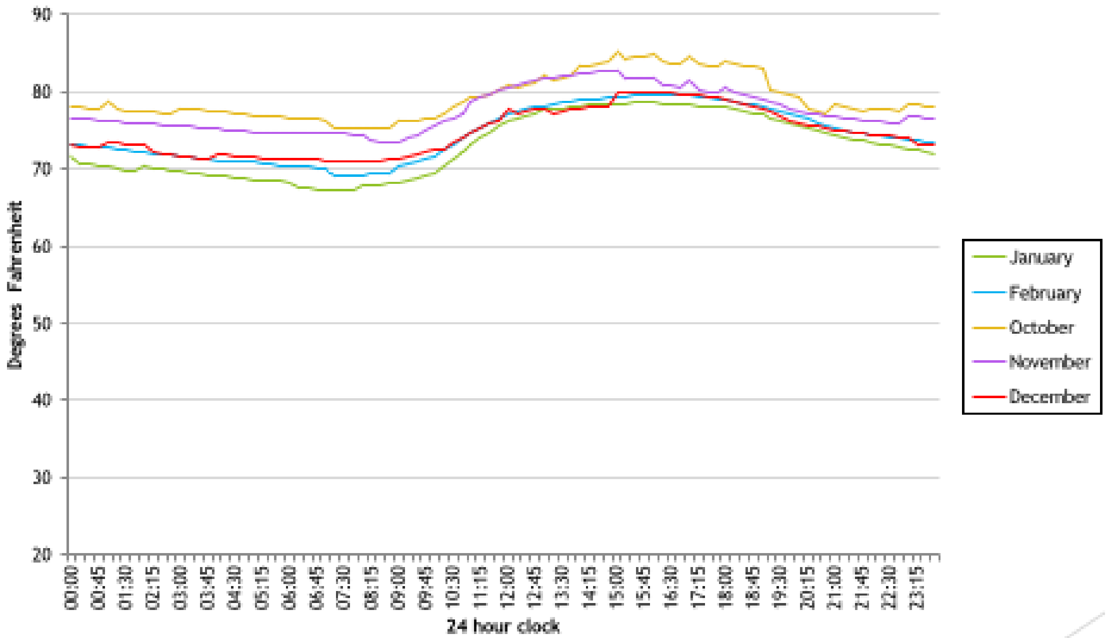
Notes: The figure displays the average daily temperature by year using data from 2014-2016. See text for more details.

Figure 2.9: Average Temperature by Season (Summer, 2014-2016)



Notes: The figure displays the average daily temperature by season using data from 2014-2016. Summer months include March, April, May, June, July, August, September, See text for more details.

Figure 2.10: Average Temperature by Season (Winter, 2014-2016)



Notes: The figure displays the average daily temperature by season using data from 2014-2016. Summer months include January, February, October, November, December. See text for more details.

Chapter 3

Examination of Individual and System Load to Understand Pricing Structure Effects on Commercial and Industrial Billing

3.1 Introduction

The aim of this paper is to investigate how load profiles of customers with different business operations align the system, and identify which industrial sectors have the most gains under an alternative pricing structure. Integration of distributed energy resources (DER) and increased electricity demand via increasing population and living standards has put pressure on the electricity grid. Maintaining the balance between energy supply with demand is critical to preserve reliability and quality of power supply.There have been efforts to maintain grid reliability through both supply and demand side management, for example, power reserve and electricity generation expansions on the power supply side, and demand response and financial incentives for the demand side, Gao Sun, 2016). Demand side management allows customers to play a role in the operation of the electricity grid by either reducing or shifting their peak demand. Studies that have investigated individual peak minimization with pricing schemes such as critical peak pricing (CPP), time of use pricing (TOU), and real time pricing (RTP) attempt to quantify the efficiency gains as electricity moves from average pricing to marginal cost pricing. Hawaiian Electric Company (HECO) has a flat rate system along with a demand and fixed charge. Hawaii currently does not have RTP. However, in 2016, HECO launched a pilot time-of-use program for residential customers who want to be charged less during the day and more for their energy use at night. HECO allowed up to 5,000 customers to be a part of this program. The goal of this initiative was to provide incentives to residential customers to shift their consumption to the daytime when renewable energy is produced.

Whether a customer can shift loads may depend on numerous factors including: their industrial classification, its operation patterns, and its price elasticity of demand. Regardless, research has shown that dynamic pricing schemes can help provide a better match between demand and supply as more renewable energy is integrated to the grid. This paper characterizes customer bill changes that occur if Hawaii shifts from a flat fate pricing to a dynamic one where retail prices reflect wholesale prices. We observe electricity consumption for large commercial and industrial sectors who are categorized under rate schedule P. This dataset will be used as an input to the simulation model of consumer electricity demand that is proposed in this paper. The welfare gains that occur under an alternative rate structure can differ between sectors and across classes of customers for various reasons. First, varying load profiles can arise due to business operation differences between each sector. Second, C&I customers also tend to have fixed business operations that are not easily altered by a change in electricity price. Finally, peak demands of consumers between sectors do not occur simultaneously and may not align with the system load, causing some sectors to gain from a dynamic pricing scheme than others. In this paper we investigate the magnitude of wealth gains under an alternative rate structure for commercial and industrial customers.

This study can serve as a learning opportunity in understanding adoption of dynamic pricing in Hawaii. The welfare gains under RTP has been a widely researched topic, and it is RTP for all customer classes that provides part of the solution to system stability with high penetration of intermittent renewable energy (Coffman, Bernstein, Wee, & Arik, 2016). Moreover, Coffman states that, "the price feedback between the utility and the customer provided by RTP helps send signals to the utility to bring additional generation online during periods of rapid rises in consumption or take them offline during periods of potential curtailment. It helps send signals to customers to encourage electricity usage when costs to generate are low and dissuade electricity usage when costs to generate are high."

On the other hand, the relationship between Individual load and the system can also serve as an input to future energy planning. Energy planning, such as future capacity requirements, is an important factor that is considered when facilitating higher peak consumption (Blonz, 2016). Recent literature that studies the coincidence between individual peaks and the system are sparse, but it is found that under a non-coincident Hopkinson rate structure, the time at which the customer pays a peak-demand charge does not necessarily coincide with the system peak (Mountain & Hsiao, 1986). However, the optimal level of system capacity is a function of average system demand and system variance, and the Hopkinson rate can be efficient if the individual maximum demand charge can reduce each user's variation in peak demand periods as well as the average demand. In addition, (Dreze, 1964) and (Veall, 1981), proved a formal analysis on how the utility can set the maximum demand charge to reduce a firms' demand variances. According to the current literature on demand charge and individual peaks, there is a need to identify when individual peaks align with the system in order to increase the effectiveness of pricing systems like demand charge and Hopkinson rate. In addition, reduction in individual peak may not only happen during peak hours but also outside peak hours. Ida et. al. (2013) finds that consumption shifts from on-peak to off-peak hours can occur when consumers face high prices during on-peak hours.

The contribution of this paper is two fold. Although there have been discussions about individual peak alignment with the system, there is little economic research that shows the economic impact of alternative pricing schemes such as RTP in the C&I sector. Among the studies that investigates the effect of an alternative pricing regime in the C&I sector (Borenstein, 2007), none have characterized the type of customers within the C&I sectors that are likely to be winners or losers from dynamic pricing. This paper investigates the impact of dynamic pricing on wealth gains, in the form of decreased customer bills, as this could also be a potential political barrier. Second, this paper fills a gap in the literature by investigating how individual load profiles align with the system load. Both contributions may serve as a method for utilities to plan for future generation and consider alternative pricing structures.

We organize the paper as follows. In section two we discuss the goals of RTP and its potential effects on individual loads. In section three, we present the theoretical framework for C&I electricity demand under price elastic and inelastic demand. In section four, we introduce the data that is utilized in the analysis. In section five we present findings from our analysis. We conclude this paper with final remarks and future research.

3.2 Alternative Billing: Dynamic Pricing Schemes

As more distributed energy resources connect to the grid, researchers have been interested in efficient pricing of electricity. The customers we study in this paper are served by Hawaiian Electricity Company, Oahu's sole energy provider. Hawaiian Electric Company's existing pricing scheme charge customers a flat volumetric rate, demand charge and fixed charge. Flat electricity rates impose standard a per kilowatt hour rate that is charged by month. On the other hand, demand charge is a dollar per kilowatt-hour rate charged based on the customer's maximum monthly kilowatt-hour demand as indicated by a demand meter. Other economists have also examined the welfare effects of time-of-use (TOU) rates, which are rates that vary depending on the time of the day. Although Hawaii had a pilot TOU program available to consumers in Oahu in 2016, the program was only available for residential customers. The customers we observe in this study are not part of a TOU program.

Current research shows that dynamic pricing schemes such as real time pricing (RTP) have potential benefits compared to TOU or flat rate pricing schemes, but the full economic impact is uncertain (Borenstein, 2005). RTP is known to be a dynamic pricing scheme because retail prices vary from hour to hour, reflecting the wholesale cost of energy generation. Significant decreases or increases in bills can occur if C&I customers were to be billed under a dynamic pricing structure. Moreover, customers under Hawaiian Electric's current billing system who have high energy consumption when wholesale prices are high are subsidized by those who consume low quantities at those times (Borenstein, 2007). RTP provides part of the solution to system reliability as more distributed energy resources are connected to the grid (Coffman et al., 2016), but winners and losers need to be taken into account when considering alternative pricing structures. In this paper, we investigate how payments change under an alternative billing regimes.

3.3 Data Sources

3.3.1 Commercial and Industrial 15-Minute Interval Consumption Data

Data are obtained from Hawaiian Electric Company (HECO) under a confidential agreement. This is a fine data set that includes a 15-minute frequency usage in both kilowatt hours (kWh) and kilowatts (kW). The data consists of C&I establishments for 2014 to 2015. The sample are large customers that have a meter and a dedicated telephone line that collects and stores data on their electrical usage at 15-minute intervals (Wordpress 2010). There are a total of 500 customers included in this data set, and is not representative of all the establishments on the island of Oahu. Rather, the data set includes a sample of large C&I customers which include: hotels, schools, hospitals, department stores, and grocery stores. Small C&I customers that are in the general non-demand rate schedule (rate G) are not included in this data set. I classify customers in this data by industrial codes, which is aligned with the North American Industrial Classification System (NAICS). The major sectors in my sample are: hotels, schools, hospitals, department stores, manufacturing and grocery stores. I observe industrial codes for all customers in the this sample.

Although there are 500 meters available for analysis, I further restrict the sample to about 121 customers. I restrict the sample to those customers who belong to rate schedule "P". According to Hawaiian Electric Company's electric rate structure, rate schedule P consists of customers who have monthly peak demand of 300 kW more three times within a given year. These customers face a higher demand charge and tend to demand a high volume of energy from the utility. The sample is restricted in this way because the simulation requires the estimation of a fixed charge under the alternative pricing structure, and customers in different rates do not face the same fixed charges. According to HECO's pricing documents, all rate schedule P customers face a fixed charge of 350 dollars, while rate J customers face varying fixed rates depending on whether they are single or three phase service customers. Customers who have PV systems are excluded from this sample as these customers have different individual loads within sectors, making those customers difficult to compare with other establishments in my sample. After deleting these customers I am left with a total of 121 C&I establishments. Table 3.1 shows the summary statistics for the restricted sample. These are the five major industries that are incorporated in the restricted sample. As present in the table, customers with the highest load share are the education and medical sectors. This can be because of heavy duty machinery located at hospitals, or the amount of air conditioning required at university campuses. Billing data are not available for this dataset, hence not presented in table 3.1.

Figure 3.1 illustrates the load share by utilizing a subsample of the MV90 dataset. This subsample consists of customers who are categorized as rate schedule P and do not have a PV system installed. Customers under rate schedule J are also omitted from this subsample. The accommodation, medical, and education sectors hold a large share of the total load. From observing the data, these sectors also have high peak demands (kW) and most likely face a higher monthly demand charge than the grocery or merchandising sectors.

To better illustrate the relationship between the individual and system loads, figure 3.2 presents the overlay of the individual and system loads. We observe that the accommodation sector has the most coincidence with the system. Specifically, the peak occurs around 8am and at night around 8pm. Other sectors do not have load profiles that coincide with the system. For example, the medical, education, merchandise, and grocery sectors experience peak demand in the daytime when solar is most available (11am to 2pm). These sectors may possibly benefit the most when introducing a marginal cost pricing as their peaks occur when the cost of generation to the utility is relatively low. Moreover, the educational sector may also benefit because the base load is low when the cost of generation for the utility is high.

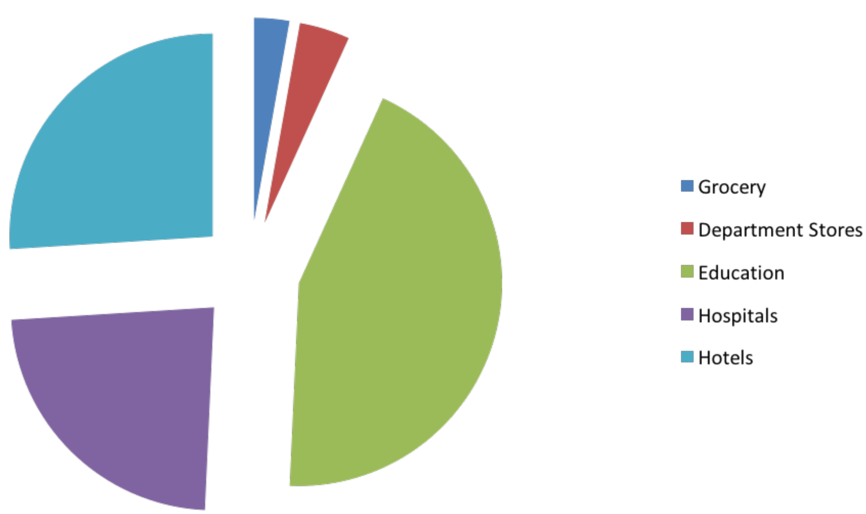
It is important to note that customers included in this data have access to their electrical usage through an internet portal. Participation in this service is voluntary, and access to data is possible through contacting a representative. Specifically, customers have data on the peak demand and energy usage trends throughout the year. Access to the data is possible through the portal at any time and this makes it easier for customers to manage demand and energy usage, documenting the impact of energy-efficient investments, and determining the impact of any new equipment or changes in operations. This information is an important aspect for the analysis because customers understand their usage behavior more than other customers who do not have access to this portal.

3.3.2 System Lambda

In addition to consumer demand data, I utilize data on the hourly generation costs that HECO faces. This is know as system lambda and obtained from the Federal Energy Regulatory Commission (FERC). System lambda includes the generation, distribution and transmission costs to the utility, and is closely related to the marginal cost of producing electricity incurred by the utility. We use this measure as a proxy to reflect the "real time" retail rate that customers in our sample face. Figure 3.3 presents the overlay of monthly effective rates with system lambda. As seen from the figure, system lambda tends to be lower than the effective rates at all year-month combination. This is most likely because the effective rates include fixed cost recovery for the utility such as servicing debt borrowed to build the plant, while the system lambda only reflects the marginal change in variable costs. Thus, for simulation purposes we incorporate a fixed charge that is charged to each customer. We explain this further in the next sections. System lambda data are available at the hourly level, but for the purpose of this figure we aggregate it to monthly measures.

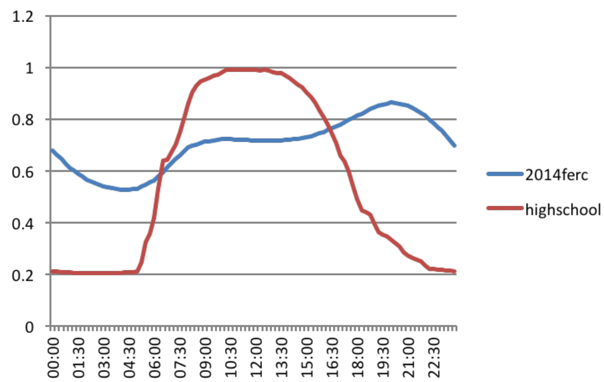
Figure 3.3 incorporates monthly system lambda, but for simulation purposes hourly measures are utilized. Hence, we also present how system lambda changes within a day. Figure 3.4 illustrates the daily average of system lambda. The figures are created using 2014 data. We utilize data from March and September to observe the seasonal differences in the system lambda. The red line represents the effective rate and is horizontal because the current customers face a flat retail rate that changes monthly not daily. The blue curve represents system lambda. When observing system lambda in March, one may notice that the peak occurs between 7am and 11 and also between 6pm and 10pm. This is not surprising as the system load profile (kWh) has peaks during these hours. The system lambda and effective rates presented here will be used as inputs to the simulation model. In addition, the system lambda plotted in figure 3.4 will serve as a comparison with the simulated electricity consumption values to better illustrate how customers respond to system lambda when they are price elastic.

Figure 3.1: Load Share by C&I Sectors for a Subsample of MV90 Csutomers (2014)

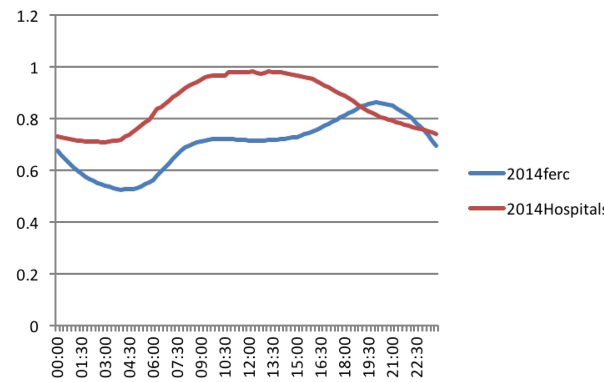


Notes: The pie chart above shows the load share (kWh) by C&I sector for 2014. The sample used to create this chart a subset of MV90 and is restricted to customers who are in rate category P and do not have PV. Rate schedule J customers are omitted from this sample. Data utilized are obtained from HECO. Load share is calculated by adding the total kWh of 2014 for all sectors.

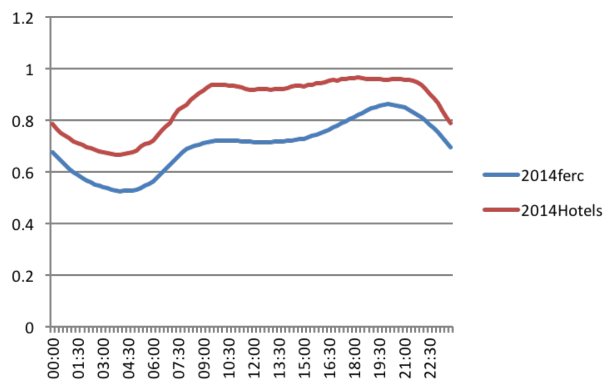
Figure 3.2: System and Individual Load Overlay



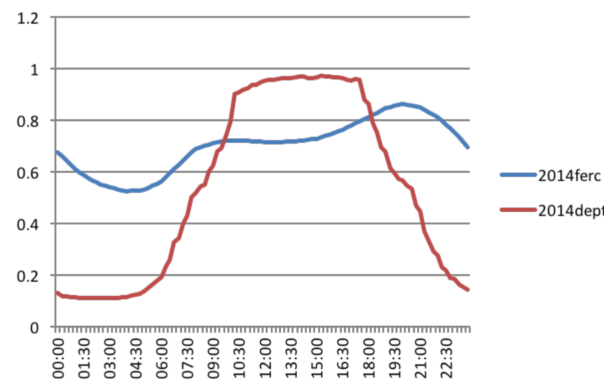
(a) Education



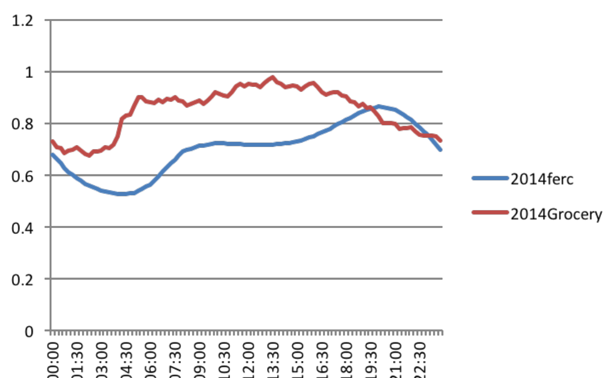
(b) Hospitals



(c) Hotels



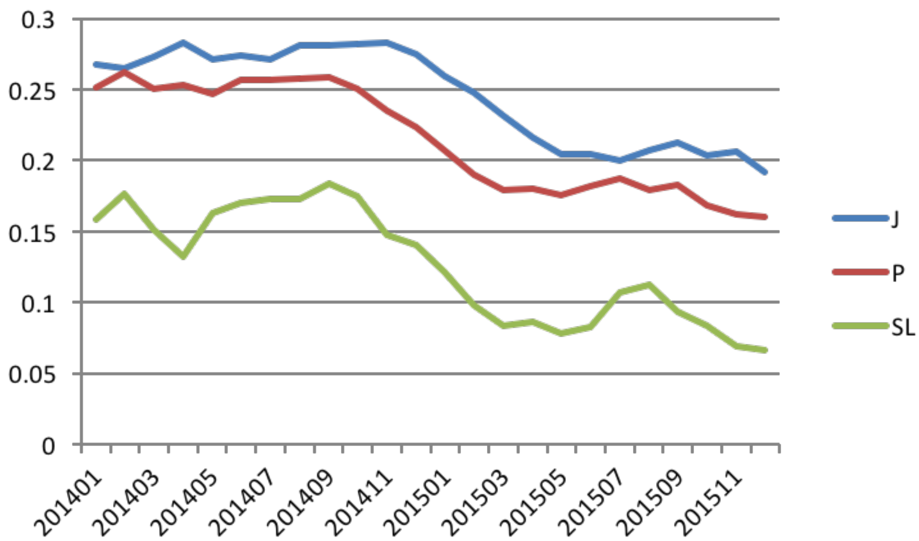
(d) General Merchandise



(e) Grocery

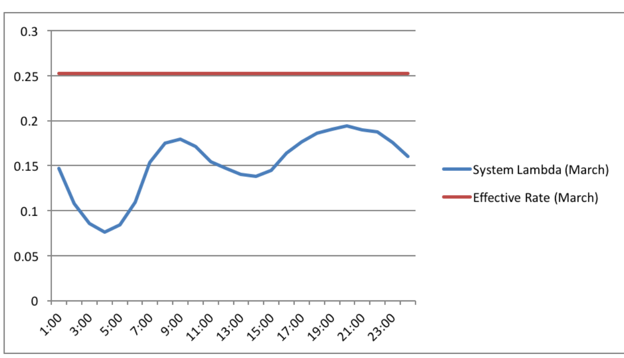
Note: Figure (a) through (e) above illustrates the overlay of system daily load and individual average daily load for all sectors. When creating these figures, customers with PV are omitted, and created based on 2014 data. Data are retrieved from FERC and HECO.

Figure 3.3: Monthly Effective Rates with System Lambda

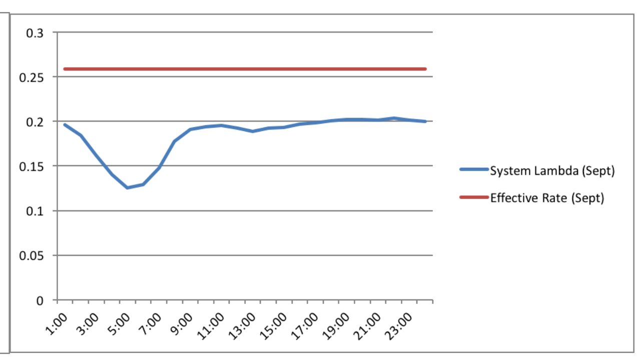


Note: The figure above shows the changes in monthly effective rates (cents/kWh) from 2014 to 2015 for rate schedules J and P, with the monthly system lambda. System lambda is available at the hourly level but is aggregated to monthly measures to accommodate the monthly effective rates. For more information on the definition of effective rates refer to the text. Effective rate information are obtained from Hawaiian Electric's public website. https://www.hawaiianelectric.com/billing-and-payment/rates-and-regulations/hawaiian-electric-rates for more details. System lambda data are retrieved from the Federal Energy Regulatory Commission (FERC).

Figure 3.4: Daily Average: System Lambda and Effective Rates



(a) System Lambda and Flat Rate (March)



(b) System Lambda and Flat Rate (September)

Note: Figure (a) above plots system lambda and effective rates for March 2014. (b) above illustrates the overlay of system lambda and effective rates. The blue curve represents the system lambda profile, and the red horizontal line represents the effective rate for the months of March and September.

Table 3.1: Summary Statistics by Sector (15-minute Usage, 2014)

	Consumption (000s kWh)		Peak Load (kW)	
	Mean	St. Dev	Mean	St. Dev
Education	321.79	706.11	1287.16	2824.44
Hospitals	385.39	382.57	1541.58	1530.29
Hotels	185.74	160.03	742.98	640.14
Merchandise	94.83	85.41	379.35	341.64
Grocery	84.22	34.63	336.9	138.54

Note: The table above presents monthly mean kWh, kW, and bill for each rate category. Standard deviation and number of firms are also presented. Data used for this table come from the MV90 portal, and the sample year is 2014. Th

3.4 Theoretical Background and Simulation Procedure

3.4.1 Constructing the Sample

When considering a dynamic rate structure, not only is the system lambda an important input to the simulation, but also customer price response to these new prices. Hence, we run the simulation by assuming two scenarios: 1) Customers have elastic price elasticity of demand, and 2) Customers have inelastic price elasticity of demand. Within these two scenarios we have sub-cases where customers are price elastic and face positive and zero demand charge, and when customers are price elastic and face positive and zero demand charge. We explain this in later sections. To construct the final sample for the simulation, we further restrict the sample to customers who don't have PV installed and are categorized as rate schedule P (customers have average monthly peak demand above 300 kilowatts). We do this for a better comparison of calculated customer bills. Using this restricted sample, CI monthly load profiles are constructed from meters that are installed in the city of Honolulu. This monthly load profile will be our starting point of the simulation process for scenario 2. Per Coffman (2016), to remove the possibility of an "income effect" we assume that if electricity consumption remained the same under the alternative structure then there will be no change in the bill that the consumer faces. The MV90 dataset is available for 2014 to 2016, but for simulation purposes we use kWh consumption data for the month where system lambda is the highest and lowest of 2014, and compare the changes in bills by sector under the following scenarios. The simulation process for both scenario is presented below.

3.4.2 Theoretical Description for Elastic Demand

This section illustrates the theory behind customer billing, and sets the stage for the simulation model of consumer electricity demand when customers are price elastic and face positive or zero demand charge. Below we explain the theory behind how the utility's bill is determined given the customer's monthly kilowatt and kilowatt-hour consumption.

Consider an optimization problem on the allocation of electricity use within a day and across days within a given billing cycle. Let h represent hour h where $h = 1, \ldots, H$ (H would be 24) and d represent day, $d = 1, \ldots, D$ (D refers to the number of days in the billing period). Let x^t_{dh} be the firm's load on day d at hour h in period t. For billing period (or "month" t) the firm's bills is given by

$$p_t \sum_{d=1}^{D} \sum_{h=1}^{H} x^t_{dh} + p_{DC}\bar{x}^t$$

where p_t is the effective (volumetric) rate for period t and $\bar{x}^t$ (the "billing demand") is given by

$$\bar{x}^t = \max\left\{\max_{d,h}\{x^t_{dh}\}, \frac{1}{2}\max_{d,h}\{x^t_{dh}\} + \frac{1}{2}\max_{s=1,\ldots,11}\{\max_{d,h}\{x^{t-s}_{dh}\}\}\right\}$$

The definition of the billing demand reflects the official rule on the demand charge:

> The maximum demand for each month shall be the maximum average load in kW during any fifteen-minute period as indicated by a demand meter. The billing demand for each month shall be the highest of the maximum demand for such month, or the mean of maximum demand for the current month and the greatest maximum demand for the preceding eleven (11) months, whichever is the higher, but not less than 300 kW.

If we think about cost minimization (given an output target), should there be daily output targets (separately for each day) or should we assume that there is an output target over the month that the firm would meet through daily outputs? The answer may depend on the sector. For simplicity, suppose there is a monthly output target $y_t \geq 0$. Then the firms' constraint when minimizing the cost of electricity use is given by

$$\sum_{d=1}^{D} \theta_t f(x_{d1}, x_{d2}, \ldots, x_{dH})) \geq y_t,$$

where θ_t represents daily fluctuations (say due to weather, weekend vs. weekdays etc.). Suppose the peak occurs on day $\bar{d}$ at hour $\bar{h}$. Then

$$x^t_{dh} \leq x_{\bar{d}\bar{h}} \quad \text{for all} \quad d, h.$$

These constraints must hold for $x_{\bar{d}\bar{h}}$ to be the peak load. The Lagrangian function is then given by

$$L = -\left(p_t \sum_{d=1}^{D}\sum_{h=1}^{H} x^t_{dh} + p_{DC}\bar{x}^t\right) + \lambda\left(\sum_{d=1}^{D}\theta_d f(x_{d1}, x_{d2}, \ldots, x_{dH})) - y_t\right) + \sum_{h,d}\left\{\mu_t(x_{\bar{d}\bar{h}} - x^t_{dh})\right\}.$$

We assume that the load profile is similar across days in that the peak hour is the same on each day and the constraint $x^t_{dh} \leq x_{\bar{d}\bar{h}}$ is not binding at all off-peak hours $h \neq \bar{h}$.

Case 1: the current month's peak exceeds the peak demand over the last 11 months

The first order condition implies

$$\frac{\partial L}{\partial x^t_{dh}} = -p_t + \lambda\theta_d f_{dh} = 0$$

for all $(d, h) \neq (\bar{d}, \bar{h})$ where $f_{dh} \equiv \partial f / \partial x^t_{dh}$. For peak hour $\bar{h}$ on the days other than $\bar{d}$ we have

$$\frac{\partial L}{\partial x^t_{d\bar{h}}} = -p_t + \lambda\theta_d f_{dh} - \mu_{d\bar{h}} = 0, \tag{3.1}$$

and at $(\bar{d}, \bar{h})$ we have

$$\frac{\partial L}{\partial x^t_{\bar{d}\bar{h}}} = -p_t - p_{DC} + \lambda\theta_{\bar{d}} f_{\bar{d}\bar{h}} + \sum_{d\neq\bar{d}}\mu_{d\bar{h}} = 0; \tag{3.2}$$

It follows from (3.1) and (3.2) that

$$P_{DC} = \sum_d \mu_{d\bar{h}}$$

for all d. This implies that $P_{DC} == D_e\mu_{d\bar{h}}$ for all d and hence

$$\mu_{d\bar{h}} = \frac{P_{DC}}{D_e}.$$

Technically speaking D_e represents the number of days over which the peak load would coincide. (This may be the number of weekdays in the billing cycle if the customer has lower peak consumption on weekends.) (Now, suppose that θ_d's are the same for all d.) For $h, h' \neq \bar{h}$ and all d, we have

$$1 = \frac{f_{dh}}{h_{d'h'}}.$$

Similarly, for any $h \neq \bar{h}$ and all d,

$$\frac{p_t}{p_t + \frac{p_{DC}}{D_e}} = \frac{f_{dh}}{h_{d\bar{h}}}$$

An important observation is that, given how the demand charge works (i.e., it is charged on the maximum load over time intervals in a day AND over days), the effective (relative) shadow price on the peak load is $\frac{p_t}{p_t + \frac{p_{DC}}{D_e}}$, not $\frac{p_t}{p_t + p_{DC}}$. Given the way the model is specified, note that

$$\frac{p_t}{p_t + \frac{p_{DC}}{D_e}} = \frac{\text{effective rate}}{\text{effective rate} + \frac{\text{demand charge}}{\text{the number of days where the peak load would coincide}}}.$$

What is the relationship between the peak load and the monthly load? With the CES functional form, we have

$$\frac{p_t}{p_t + \frac{p_{DC}}{D_e}} = \frac{\theta_d \beta_h x_{dh}^{\rho-1}}{\theta_{\bar{d}} \beta_{\bar{h}} x_{\bar{d}\bar{h}}^{\rho-1}}$$

for all d, h. Solve this for the ratio of electricity load:

$$\frac{x_{dh}}{x_{\bar{d}\bar{h}}} = \left(\frac{\beta_h}{\beta_{\bar{h}}}\right)^{\sigma} \left(\frac{p_t}{p_t + \frac{p_{DC}}{D_e}}\right)^{-\sigma},$$

where $\sigma \equiv 1/(1-\rho)$.

Add both sides over all hours on day $\bar{d}$ to obtain

$$\frac{\sum_h x_{\bar{d}h}}{x_{\bar{d}\bar{h}}} = 1 + \frac{\sum_{h \neq \bar{h}} \beta_h^{\sigma}}{\beta_{\bar{h}}^{\sigma}} \left(\frac{p_t}{p_t + \frac{p_{DC}}{D_e}}\right)^{-\sigma},$$

Then sum this expression over all days over the billing cycle:

$$\frac{\sum_d \sum_h x_{dh}}{x_{\bar{d}\bar{h}}} = D \left\{ 1 + \frac{\sum_{h \neq \bar{h}} \beta_h^{\sigma}}{\beta_{\bar{h}}^{\sigma}} \left(\frac{p_t}{p_t + \frac{p_{DC}}{D_e}}\right)^{-\sigma} \right\}.$$

This implies that, with a load factor regression, we have

$$\ln\left(\frac{\sum_d \sum_h x_{dh}}{x_{\bar{d}\bar{h}}}\right) = C - \sigma \ln\left(\frac{p_t}{p_t + \frac{p_{DC}}{D_e}}\right)$$

or

$$\ln\left(\frac{x_{\bar{d}\bar{h}}}{\sum_d \sum_h x_{dh}}\right) = C' - \sigma \ln\left(\frac{p_t + \frac{p_{DC}}{D_e}}{p_t}\right).$$

Hence, if we regress the load factor on the ratio of the effective rate plus (demand charge - effective rate, divided by the number of billing days to the effective rate, then the coefficient would indicate the elasticity of substitution.

Case 2: the current month's peak is lower than the peak demand over the last 11 months

In this case, the Lagrangian function is given by

$$L = -\left(p_t \sum_{d=1}^{D}\sum_{h=1}^{H} x_{dh}^t + p_{DC}\left\{\frac{1}{2}\max_{d,h}\{x_{dh}^t\} + \frac{1}{2}\max_{s=1,\ldots,11}\{\max_{d,h}\{x_{dh}^{t-s}\}\}\right\}\right)$$

$$+\lambda\left(\sum_{d=1}^{D}\theta_d f(x_{d1}, x_{d2}, \ldots, x_{dH})) - y_t\right) + \sum_{h,d}\left\{\mu_t(x_{\bar{d}\bar{h}} - x_{dh}^t)\right\}.$$

As the expression indicates, the marginal price of the maximum load in this case is $\frac{P_{DC}}{2}$ instead of P_{DC}. Therefore, the effective shaedow price of the peak load consumption is lower: for any $h \neq \bar{h}$ and all d,

$$\frac{p_t}{p_t + \frac{p_{DC}}{2D_e}} = \frac{f_{dh}}{h_{\bar{d}\bar{h}}}.$$

3.4.3 Load factor regression

It is important to note that in this scenario we assume that changes in demand by the customers in our sample does not affect generation. We calculate the share of monthly total load and take the ratio between this and the system load. We find that the share is less than 0.05% in any given month. This justifies the simplifying assumption that the changes in the load for the sample customers will not change the system lambda or marginal costs. The load factor regression model is presented by the following:

$$ln(S_{it}) = \beta_1 * X * G + \beta_2 * X + \beta_3 * G + \beta_4 * PV_{it} + \beta_p * D_{itp} + \alpha_y + \mu_m + \eta_i + \epsilon_{it}, \tag{3.3}$$

where $ln(S_{it})$ is representative of the load factor and is calculated as the ratio of total kWh consumed in a designated period by the product of the maximum demand in kW and the number of days in the billing period:

$$S_{it} = \frac{X^t}{\max_{dh} x^t_{dh}}.$$

The variable X represents the ratio of the off-peak and peak prices, but this should be adjusted based on the discussion above.

To clarify on the correct price ratio, we list the rule on the demand charge again:

> The maximum demand for each month shall be the maximum average load in kW during any fifteen-minute period as indicated by a demand meter. The billing demand for each month shall be the highest of the maximum demand for such month, or the mean of maximum demand for the current month and the greatest maximum demand for the preceding eleven (11) months, whichever is the higher, but not less than 300 kW.

Hence,

$$X_t = \frac{p_{t-1}}{p_{t-1} + \frac{p_{DC}}{D_e}}$$

if the maximum demand for the current month exceeds or is equal to the greatest maximum demand for the preceding 11 months and

$$X_t = \frac{p_{t-1}}{p_{t-1} + \frac{p_{DC}}{2D_e}}$$

otherwise (that is, if the maximum demand for the current month is lower than the greatest maximum demand for the preceding 11 months. For the purpose of the regression with monthly billing data, D_e could be equal to 20 for all observations for simplicity.

Suppose the firm's production function is given by:

$$y = A\left\{\alpha z^{\theta} + (1-\alpha)q^{\theta}\right\}^{1/\theta},$$

$$q = \phi\left\{\sum_{h=1}^{H} \beta_h x_h^{\rho}\right\}^{1/\rho},$$

where q is the input of electricity services and z is the quantity of the composite of other factors of production. The parameter θ determines the elasticity of substitution between the composite factor and electricity, $\sigma \equiv 1/(1-\theta)$. Note that σ also influences the own price elasticity of the electricity demand. On the other hand, ρ determines the size of the elasticity of substitution (e.g., inter-hour substitution of electricity) $\sigma_e \equiv 1/(1-\rho)$.

From the first-order conditions of cost minimization subject to minimum output q, we have:

$$\frac{x_{h'}}{x_h} = \left(\frac{p_{h'}}{p_h}\frac{\beta_{h'}}{1-\beta_h}\right)^{\sigma_e}.$$

This equation indicates the following specification to estimate the relative demand:

$$\ln\left(\frac{x_1}{x_2}\right) = C + \sigma_e \ln\left(\frac{p_2}{p_1}\right) + \varepsilon,$$

where $C \equiv \sigma_e \ln\left(\frac{\beta}{1-\beta}\right)$ (that is a regression of the log of the ratio of the off-peak load to the peak load on the log of the ratio of the peak price to the off-peak price).

Let $w > 0$ be the unit price of the composite input and p_e the price index of electricity. With manipulation, we obtain the marginal cost of production $c(w,p)/A$ where

$$c(w, p_e) = \left\{\alpha^{\sigma} w^{1-\sigma} + (1-\alpha)^{\sigma} p_e^{1-\sigma}\right\}^{\frac{1}{1-\sigma}}.$$

The above cost-minimization solution implies that the payment for electricity service q is given by:

$$p_e q = (\phi) = hc(w, p_e)y/A,$$

where where h is the factor payment share defined by:

$$h \equiv \frac{(1-\alpha)^{\sigma} p_e^{1-\sigma}}{\alpha^{\sigma} w^{1-\sigma} + (1-\alpha)^{\sigma} p_e^{1-\sigma}}.$$

With the assumption of constant returns to scale, the profit-maximizing output level y is indeterminate. If the industry is subject to monopolistic competition, then the firm's equilibrium output price P_o is a markup over its marginal cost where the markup rate depends on the elasticity of (consumption) substitution across the goods produced in the industry:

$$P_o = \frac{c(w, p_e)}{\rho^c A},$$

where ρ^c captures representative consumers' preference such that $1/(1-\rho^c)$ is the elasticity of consumption substitution. The corresponding profit-maximizing output choice satisfies

$$y = Y \left\{ \frac{P_o \rho \phi}{c(w, p_e)} \right\}^{\sigma},$$

where Y is the industry-level output index. Substitute this expression into **??**, and recall that $p_1 = p$ (the volumetric rate) and $p_2 = p + p_D$ (the volumetric rate plus the demand charge) and we obtain an expression for the elasticity of demand with respect to the volumetric rate:

$$\frac{\partial X}{\partial p} \frac{p}{X} = -\sigma.$$

That is, Under the assumption, the demand charge does not influence the elasticity. This forms one of the null hypotheses of the analysis below.

Turning to the allocation of electricity, the CES property of the technology implies

$$p_1 x_1(\phi) = h_1 c_e(p_1, p_2) q / \phi,$$

where h_1 is the factor payment share on electricity in period 1, defined by:

$$h \equiv \frac{\beta^{\sigma_e} p_1^{1-\sigma_e}}{\beta^{\sigma_e} p_1^{1-\sigma_e} + (1-\beta)^{\sigma_e} p_2^{1-\sigma_e}},$$

and $c_e(p_1, p_2) = \{\beta^{\sigma_e} p_1^{1-\sigma_e} + (1-\beta)^{\sigma_e} p_2^{1-\sigma_e}\}^{\frac{1}{1-\sigma_e}}$. Taken together, the demand for electricity is given by

$$x_1 = \beta^{\sigma_e} p_1^{-\sigma_e} \{\beta^{\sigma_e} p_1^{1-\sigma_e} + (1-\beta)^{\sigma_e} p_2^{1-\sigma_e}\}^{\frac{\sigma_e - \sigma}{1-\sigma_e}} C,$$

$$x_2 = (1-\beta)^{\sigma_e} p_2^{-\sigma_e} \{\beta^{\sigma_e} p_1^{1-\sigma_e} + (1-\beta)^{\sigma_e} p_2^{1-\sigma_e}\}^{\frac{\sigma_e - \sigma}{1-\sigma_e}} C,$$

where C is a constant term.

3.5 Scenario 1: Simulation Procedure Under Elastic Demand

Now that we are familiar with the theory behind the determinants of customer bill and pricing structure, we move to the simulation procedure when customers are price elastic. Below illustrates how to construct a demand function that allows consumers to be price elastic under RTP. Suppose we pick a month where the peak consumption (the maximum demand) exceeds the maximum demand over the last 11 months. Then the ratio of the off-peak and the peak consumption (for a particular day) is given by

$$\frac{\sum_{h \neq \bar{h}} x_{\bar{d}h}}{x_{\bar{d}\bar{h}}} = \frac{\sum_{h \neq \bar{h}} \beta_h^{\sigma_e}}{\beta_{\bar{h}}^{\sigma_e}} \frac{p_t^{-\sigma_e}}{\left(p_t + \frac{p_{DC}}{D_e}\right)^{-\sigma_e}}. \tag{3.4}$$

Normalize β_h's so that

$$\sum_{h=1}^{H} \beta_h^{\sigma_e} = \left(\sum_{h \neq \bar{h}} \beta_h^{\sigma_e}\right) + \beta_{\bar{h}}^{\sigma_e} = 1.$$

Then it follows from (3.4) that

$$\frac{\sum_{h \neq \bar{h}} x_{\bar{d}h}}{x_{\bar{d}\bar{h}}} = \frac{1 - \beta_{\bar{h}}^{\sigma_e}}{\beta_{\bar{h}}^{\sigma_e}} \frac{p_t^{-\sigma_e}}{\left(p_t + \frac{p_{DC}}{D_e}\right)^{-\sigma_e}}.$$

What should D_e be? It represents the number of days in a billing cycle when the load is close to the maximum demand. If a customer operates in a similar manner from Monday to Friday (with lower electricity consumption in the weekend), then D_e would represent the number of weekdays in the billing period. We could approximate it by $5 * 4 = 20$. (NOTE: For an industry where the weekday and weekend consumption patterns are similar, with similar peak consumption, D_e should be the number of all days in the billing period.)

The above equality indicates

$$x_{d\bar{h}} p_t^{-\sigma_e} - x_{d\bar{h}} p_t^{-\sigma_e} \beta_{\bar{h}}^{\sigma_e} = \sum_{h \neq \bar{h}} x_{\bar{d}h} \left(p_t + \frac{p_{DC}}{D_e} \right)^{-\sigma_e} \beta_{\bar{h}}^{\sigma_e}$$

and hence

$$\beta_{\bar{h}}^{\sigma_e} = \frac{x_{d\bar{h}} p_t^{-\sigma_e}}{\sum_{h \neq \bar{h}} x_{\bar{d}h} \left(p_t + \frac{p_{DC}}{D_e} \right)^{-\sigma_e} + p_t^{-\sigma_e} x_{d\bar{h}}}.$$

This is how we can pin down the value of $\beta_{\bar{h}}^{\sigma_e}$. We also note that

$$\frac{x_{\bar{d}h}}{x_{d\bar{h}}} = \frac{\beta_h^{\sigma_e}}{\beta_{\bar{h}}^{\sigma_e}} \frac{p_t^{-\sigma_e}}{\left(p_t + \frac{p_{DC}}{D_e} \right)^{-\sigma_e}}$$

for all $h \neq \bar{h}$. Solve for $\beta_h^{\sigma_e}$ to obtain

$$\beta_h^{\sigma_e} = \frac{x_{\bar{d}h}}{x_{d\bar{h}}} \frac{\left(p_t + \frac{p_{DC}}{D_e} \right)^{-\sigma_e}}{p_t^{-\sigma_e}} \beta_{\bar{h}}^{\sigma_e}$$

for all $h \neq \bar{h}$.

Once β_h's are identified, we can compute the electricity consumption for all hours.

For off-peak h, we have

$$x_{dh} = \beta_h^{\sigma_e} p_t^{-\sigma_e} \left\{ \left(\sum_{h \neq \bar{h}} \beta_h^{\sigma_e} \right) p_t^{1-\sigma_e} + \beta_{\bar{h}}^{\sigma_e} \left(p_t + \frac{p_{DC}}{D_e} \right)^{1-\sigma_e} \right\}^{\frac{\sigma_e - \sigma}{1-\sigma_e}} C,$$

where C is a constant. At the peak hour, the consumption satisfies

$$x_{d\bar{h}} = \beta_{\bar{h}}^{\sigma_e} \left(p_t + \frac{p_{DC}}{D_e} \right)^{-\sigma_e} \left\{ \left(\sum_{h \neq \bar{h}} \beta_h^{\sigma_e} \right) p_t^{1-\sigma_e} + \beta_{\bar{h}}^{\sigma_e} \left(p_t + \frac{p_{DC}}{D_e} \right)^{1-\sigma_e} \right\}^{\frac{\sigma_e - \sigma}{1-\sigma_e}} C.$$

According to the theory above, the demand for electricity is modeled with own-price elasticity with both -0.10 and -0.20, and we assume a substitution elasticity parameter of 0.15 from Coffman (2016). The simulation results will present tables that incorporate these two own price elasticities.

3.5.1 Customers are price elastic and face positive demand charge

Section five explains the simulation under elastic demand, but does not mention how demand charge can play a role when constructing bills under RTP. In this subsection we consider the case where customers face a demand charge under RTP and are price elastic. When calculating the bill under RTP, we use a simple equation that adds the volumentric payment bill under RTP with the calculated fixed charge and add the demand charge portion of the bill. The demand charge is equal to the demand charge under the current bill. There are two differences between the case when customers are price elastic and face a demand charge and when they don't: 1) The calculation of the fixed cost portion of the RTP bill; 2) The demand charge payment is added to the bill under RTP. Below the fixed charge calculation and alternative bill construction is explained.

When calculating the fixed charge portion of the bill under elastic demand and positive demand charge, we consider the following equation:

$$BRfc = \frac{\sum_j \sum_i BCvol_{ij} - \sum_j \sum_i BRvol_{ij} + \sum_j \sum_i BCdc_{ij}}{\text{number of all customers in the sample}}$$

where $\sum_j \sum_i BRvol_{ij}$ is equal to the summation of the volumetric portion of the bill under RTP summed by individual i and sector j. $BCdcij$ is the demand charge payment by customer i in sector j, where $BRdc_{ij}$ is equal to $BCdcij$. Finally, $\sum_j \sum_i BCvol_{ij}$ indicates that the volumetric payment under the current bill is summed by customer and sector. Thus, we construct the bill when customers are price elastic and face positive demand charge as the following:

$$BR_{ij} = BRvol_{ij}^{t} + BRdc_{ij} + BRfc.$$

Where $BRdc_{ij}$ is equal to $BCdc_{ij}$.

Next we navigate the "pure RTP" case where customers are price elastic and do not face a demand charge.

3.5.2 Customers are price elastic and face zero demand charge

In this section we look at consumption under the case under pure RTP where customers are elastic but do not face a demand charge. This is simply an alternative version of the content presented in subsection 5.1. The fixed cost under this case is calculated without adding the demand charge portion of the bill and is presented below:

$$BRfc = \frac{\sum_j \sum_i BCvol_{ij} - \sum_j \sum_i BRvol_{ij}}{\text{number of all customers in the sample}}$$

Thus, pure RTP is the case where the fixed cost is by taking the difference between the volumetric portion of the bill under RTP and current and dividing by the total number of customers in the sample. $BRfc$ is then added with the volumetric portion of the bill under RTP to generate the total bill when customers face a dynamic rate structure:

$$BR_{ij} = BRvol_{ij}^t + BRdc_{ij} + BRfc.$$

where $BRdc_{ij}$ is equal to zero. It is important to note that the fixed charge under the case where demand charge is positive is going to be smaller than the case when demand charge is zero. The equalities presented in subsections 5.1 and 5.2 will be utilized when examining the percent change in customer billing when switched from the current rate to the dynamic rates.

The next section illustrates the simulation process when: 1) customers are price inelastic and face a demand charge; and 2) are price inelastic and do not face a demand charge. The next section also considers the cases where customers face zero and positive demand charge.

3.6 Scenario 2: Simulation Procedure Under Inelastic Demand

In this section we present the simulation procedure under inelastic demand. Bills under RTP are calculated using two methods under this scenario. In the first case, we calculate RTP bills assuming that customers do not face a demand charge. Thus, bills are calculated by simply adding the product of the system lambda and monthly electricity consumption with the calculated fixed cost. In the second case, RTP bills are calculated under the assumption that customers face a demand charge. Hence, this procedure will give an idea as to how customers bill change under the RTP when they are facing an extra cost (demand charge).

Using the restricted dataset as explained above in the "constructing the sample" subsection, we run the simulation by assuming customers are price inelastic. We adopt the simulation procedure by Borenstein (2007) for this scenario. We calculate electricity bills for each sector in the sample using wholesale prices (system lambda) obtained by FERC and look at their payments under an alternative regime. Because dynamic pricing charge customers based on marginal cost rather than average, the system lambda will provide a reasonable estimate of what value the customer will be charged under an alternative rate structure (see section on data sources). Throughout the simulation we assume that electricity consumption stays the same under the current billing structure and the alternative one. As per Borenstein (2007), the simulation model accounts for variable and fixed cost recovery for the utility. However, unlike Borenstein, we do not simulate wholesale costs, but rather utilize actual system lambda data from 2014 to calculate customer bills. Each sectors' bill under the alternative billing structure will be compared with their payments under the current flat rate system. It is expected that under this scenario some sectors will experience an increase in their bills, while others decrease.

Below we present the theoretical basis of how bills will be calculated under RTP and the current pricing scheme.

For each customer i in industry j, the bill under the current rate will be calculated as the following: Let h represent hour h where $h = 1, \ldots, H$ (H would be 24) and d represent day, $d = 1, \ldots, D$ (D refers to the number of days in the billing period). Let x^t_{dh} be the firm's load on day d at hour h in period t. Consider the electricity payment by customer i in sector (industry) j. Let

$$BCvol_{ij} = p_t \sum_{d=1}^{D} \sum_{h=1}^{H} x^t_{dh,ij}$$

be the energy charge (or the volumetric rate payment) under the current bill, where p_t is the flat volumetric rate. Let

$$BCdc_{ij} = p_{DC} \bar{x}^t_{ij}$$

represent the demand charge payment under the current bill. (Customers pay for fixed charge under the current bill, but we omit that from our analysis.) Hence, the current bill is the sum of the volumetric and demand charge payment.

$$BC_{ij} = BCvol_{ij} + BCdc_{ij}.$$

Next, given the observed load profile $\{x^t_{dhij}\}$, compute the bill under RTP $\{p^t_{dh}\}$. Let

$$BRvol^t_{ij} = \sum_{d=1}^{D} \sum_{h=1}^{H} p^t_{dh} x^t_{dh}$$

be the variable portion of the RTP payment. Let $BRfc$ be the fixed charge under RTP. Let $BRdc$ be the demand charge. Then the total payment under RTP for customer i in sector j is

$$BR_{ij} = BRvol^t_{ij} + BRdc_{ij} + BRfc.$$

The value of $BRdc_{ij}$will vary depending on the case: 1) customers are price elastic and face zero demand charge; and 2) customers are price elastic and face positive demand charge. We present how to calculate the fixed charge under this case below.

3.6.1 Customers are price inelastic and face zero demand charge

This is the base case where customers do not face a demand charge under RTP. Specifically, the simulation is conducted by utilizing the method presented in section 5 but $BRdc_{ij} = 0$. Hence, bills under RTP are simply calculated as the sum of calculated fixed charge and the variable portion of the RTP bill:

$$BR_{ij} = BRvol^t_{ij} + BRfc.$$

Current bills are calculated using the method presented in section 5. Next we move to the scenario when customers are price inelastic and face a positive demand charge.

3.6.2 Customers are price inelastic and face positive demand charge

In order to construct the bill under RTP, we need to calculate the fixed cost so it reflects the demand charge. In this case, we assume $BRdc_{ij}$ is the same as in $BCdcij$. That is, we consider RTP where the demand charge is also specified in the same way as under the current bill. It is important to note that the fixed charge under RTP should be set so that the aggregate payments by all customers are the same under the current rate and RTP:

$$\sum_j \sum_i BC_{ij}^t = \sum_j \sum_i BR_{ij}^t.$$

In this case the fixed charge under RTP is computed as such:

$$\sum_j \sum_i BRfc = sum_j \sum_i BCvol_{ij} - \sum_j \sum_i BRvol_{ij} + \sum_j \sum_i BCdc_{ij}.$$

where $BRdc_{ij}$ is equal to $BCdcij$. Hence the fixed charge for each customer is computed by utilizing the equation below.

$$BRfc = \frac{\sum_j \sum_i BCvol_{ij} - \sum_j \sum_i BRvol_{ij} + \sum_j \sum_i BCdc_{ij}}{\text{number of all customers in the sample}}$$

Thus, the bill under RTP is equal to:

$$BR_{ij} = BRvol_{ij}^t + BRdc_{ij} + BRfc.$$

where $BRdc_{ij}$ is equal to $BCdcij$.

3.6.3 Decomposition of bill changes when customers face an alternative pricing structure.

However, we need to address the question of whether customers are increasing or decreasing consumption because of a price level change or fixed cost change, We include an equation that illustrates the breakdown of the change in bills into: fixed charge portion, the price level portion and price variation portion. This method is also applied to the case when customers are price elastic and face zero or positive demand charge.

The calculation is as follows: For each month t, compute α_t such that

$$\sum_j \sum_i BCvol_{ij}^t = \alpha_t \sum_j \sum_i BRvol_{ij}^t.$$

That is, α_t times the total RTP bill (for all customers in all sectors) in month t is equal to the actual current total bill in the same month:

$$\alpha_t = \frac{\sum_j \sum_i BCvol_{ij}^t}{\sum_j \sum_i BRvol_{ij}^t}.$$

Note that the change in the bill by going from the current bill to RTP for customer i in sector j is given by

$$BR_{ij}^t - BC_{ij}^t = BRvol_{ij} + BRdc_{ij} + BRfc - (BCvol_{ij} + BCdc_{ij})$$

$$= BRvol_{ij} - BCvol_{ij} + BRfc = BRvol_{ij} - \alpha BRvol_{ij} + \alpha BRvol_{ij} - BCvol_{ij} + BRfc$$

$$= \sum_d \sum_h p_{dh} x_{dh} - \sum_d \sum_h \alpha p_{dh} x_{dh} + \sum_d \sum_h \alpha p_{dh} x_{dh} - \sum_d \sum_h p x_{dh} + BRfc$$

In the expression on the last line, the first two term is (a) the effect due to a change in the level of the prices, (b) the third and the fourth terms represent the effect due to variations in prices, and (c) the last term due to change in the fixed pay.

3.7 Simulation Results

This section presents the calculated electricity bills for C&I customers under alternative rates from two scenarios: when customers are price elastic and inelastic. The simulated bills include the charge for transmission and distribution (see data section above) as well as the fixed costs to the utility. For each scenario we compare each sector's bill under dynamic pricing to their payments under the current billing schedule.

3.7.1 Scenario 1: Price Elastic Case

Here we present the simulation results when customers are price elastic. First, we present tables 3.2, 3.3, 3.4 and 3.5 that show the percentage of surplus or loss that each sector faces in terms of the changes in electricity bills when introduced to an alternative pricing structure. We run separate simulations for March and September of 2014, two months when system lambda is the highest and lowest, respectively. There are four tables–two for each month because we consider the case when customers face zero and positive demand charge.The tables present simulations from two different values of the own price elasticity to allow for flexibility in customer price response. The two values considered are an elasticity of -0.10 and -0.20.

Table 3.2 and 3.3 represents the case where customers are price elastic and face positive demand charge. The fixed charge is calculated as illustrated section 5. Table 3.2 and 3.4 utilizes data from march, while 3.3 and 3.5 use data from September.

When comparing tables 3.2 and 3.3 we notice several key points. One, all sectors except for the educational sector have high bill totals under the current rate in September than in March. This could be because customers use more energy during hot months via increased air conditioning demand. The educational sector possibly face lower current bills in September because students are not in school during the summer break. Most sector face higher bills not only because they consume more during hot months but also because system lambda is higher during the day compared to March levels (see figure 3.4). Two, when examining the differences between months (figures 3.2 and 3.3) we find that sectors who are considered "winners" of RTP benefit from RTP more in March than in September. Moreover, sectors who are considered "losers" under RTP, such as grocery hotels and department stores, tend to experience higher bills under RTP in September than in March. This is because losers from RTPnot only have higher current bills in September, but also an increase in alternative bills causing the gap between current and alternative to expand further.The increase in alternative bills in September can be due to either an increase in the demand charge or the volumetric payment of the bill. Especially when electricity demand tends to rise during the hottest months. Last, regardless of the month, alternative bills tend to decrease when customers have an own price elasticity of -0.2 relative to -0.1.

Next, we compare tables 3.4 and 3.5 that presents the percent change in bills when customers switch to an alternative bill. Key points from the paragraph above also tend to hold here with September bills under current rates being higher for all sectors except for education. One key difference between the case where customers face positive and zero demand charge under RTP is that the alternative bills are significantly lower under the case where demand charge is zero. This is not surprising as the demand charge payment is not included when calculating the bills under RTP when demand charge is zero. Another key aspect of tables 3.4 and 5 are that the hotel sector shifts from loser to winner when they are faced with zero demand charge. In tables 3.2 and 3.3, the accommodation faced a slight increase in alternative bills under positive demand charge. However, this sector benefits from the ease in bills when the demand charge is not added to their RTP bills. Hence, based on these four tables, incorporation of demand charge in the alternative rates can certainly hurt sectors compared to the case when demand charge is zero.

The four tables mentioned above only illustrate tee percent change in bills under the two rate structures, and do not consider the decomposition of the change. The decrease or increase in alternative bills can stem from a price effect (since system lambda is lower than effective rates) or it could be due to the magnitude of the fixed payment. Tables 3.6 and 3.7 address these questions by presenting the breakdown of the change in bills into three components: the price level effect, price variation effect, and the fixed charge effect. The price level effect is the effect that arises from lowered volumetric rates. The price variation effect is the effect of changes in electricity consumption that arises fro the variation in system lambda between hours.

Table 3.6 shows this breakdown for September when customers face zero demand charge. Consistent with the previous tables, the sectors who experience the most benefits from RTP are the education and medical sectors with an average change in bills of -27,000 and -20,000 dollars, respectively. When comparing the effect of the own price elasticity, the average change in bills seem to be less when customers are more price responsive. Meaning that sectors have less benefits or more costs when they are more price elastic. Table 3.7 presents the decomposition for September bill when customers face positive demand charge. Based on the results in tables 3.2-3.5, it is no surprise that the average change in bills, price level effect and price variation effects are larger under positive demand charge. This is because the gap between current and alternative bills increases as demand charge is added to the alternative bills while the current bill stays the same. One important note is that the fixed charge is lower in the case where demand charge is equal to zero because the demand charge is added to the volumetric rate when calculating the fixed charge, causing the gap between BC_vol and BR_vol to widen. Hence, although customers face a lower fixed charge when demand charge is positive, the average increase in or decrease in bills under RTP the demand charge effect is too large to cancel the benefit of a lower fixed charge.

To provide a comparison of load profiles under the alternative (both positive and zero demand charge cases) and current rate structures, we use the simulated consumption values and plot them with the actual consumption (kWh). Figure 3.5 illustrates the two load profiles using electricity consumption from March. A note is that the figures are not normalized. The green line illustrates the simulated load without the demand charge, the red line the simulated load profile with demand charge, and the blue line representing the load utilizing the actual consumption. As illustrated in the figure, the load profiles under the alternative rates with and without demand charge differ from that of the actual load profile for all sectors. By theory, customers increase demand under RTP because the system lambda is lower than the effective rates at all hours. In addition, the load profile under positive demand charge is lower than the case where customers face zero demand charge. This could be because customers have an incentive to demand less because they will be penalized via higher demand charge payment. Another aspect to notice is the shift in peak. Customers tend to be shifting their consumption to hours when the system lambda is lowest. For example, the accommodation sector has peak load at about 3:30 PM when the system lambda for March is the lowest. The same phenomenon exists with the grocery, medical and educational sectors where the peak load occurs at around 3PM. All load profiles are averaged at each hour. I include individual load profiles that are not aggregated in appendix B (figure 3.7). A customer from each sector is pick randomly to create these figures.

Table 3.2: Change in Bills when Customers are Price Elastic and face positive demand charge (March Bills)

	Current (mil)	Alternative (mil)	Change in bills(%)	# of firms
sigma=0.10				
Education	$11.5	$9.7	-17.9%	35
Hospitals	$ 4.9	$4.3	-13.9%	15
Hotels	$5.7	$6.1	6.5%	38
Merchandise	$1.5	$2.0	25.0%	17
Grocery	$1.2	$1.8	35.1%	17
sigma=0.20				
Education	$11.5	$9.6	-16.5%	35
Hospitals	$4.9	$4.2	-16.6%	15
Hotels	$5.7	$6.0	5.0%	38
Merchandise	$1.5	$1.9	23.3%	17
Grocery	$1.2	$1.8	33.3%	17

Note: The table above presents the bill change when customers are price elastic. Simulated values (demand) come from the model presented in section 4. The sample used for this table are customers who are categorized as rate P. Moreover, the sample period is March of 2014, when system lambda is at its lowest of 2014. System lambda are obtained from FERC.

Table 3.3: Change in Bills when Customers are Price Elastic and face a positive demand charge (September Bills)

	Current (mil)	Alternative (mil)	Change in bills(%)	# of firms
sigma=0.10				
Education	$10.1	$9.9	-2.0%	35
Hospitals	$5.3	$5.0	-6.0%	15
Hotels	$6.5	$7.2	9.7%	38
Merchandise	$1.5	$2.1	28.5%	17
Grocery	$1.3	$2.0	35%	17
sigma=0.20				
Education	$10.1	$9.7	-4.1%	35
Hospitals	$ 5.3	$4.9	-8.1%	15
Hotels	$6.5	$7.2	9.7%	38
Merchandise	$1.5	$2.1	28.5%	17
Grocery	$1.3	$2.0	35%	17

Note: The table above presents the bill change when customers are price elastic. Simulated values (demand) come from the model presented in section 4. The sample used for this table are customers who are categorized as rate P. Moreover, the sample period is September of 2014, when system lambda is at its lowest of 2014. System lambda are obtained from FERC.

Table 3.4: Change in Bills when Customers are Price Elastic and ZERO demand charge (March Bills)

	Current (mil)	Alternative (mil)	Change in bills(%)	# of firms
sigma=0.10				
Education	$11.5	$8.6	-33.7%	35
Hospitals	$ 4.9	$3.9	-25.6%	15
Hotels	$5.7	$5.4	-5.5%	38
Merchandise	$1.5	$1.7	11.7%	17
Grocery	$1.2	$1.6	25%	17
sigma=0.20				
Education	$11.5	$7.4	-55.4%	35
Hospitals	$4.9	$3.2	-53.1%	15
Hotels	$5.7	$4.9	-16.3%	38
Merchandise	$1.5	$1.6	6.2%	17
Grocery	$1.2	$1.5	20%	17

Note: The table above presents the bill change when customers are price elastic. Simulated values (demand) come from the model presented in section 4. The sample used for this table are customers who are categorized as rate P. Moreover, the sample period is March of 2014, when system lambda is at its lowest of 2014. System lambda are obtained from FERC.

Table 3.5: Change in Bills when Customers are Price Elastic and face ZERO demand charge (September Bills)

	Current (mil)	Alternative (mil)	Change in bills(%)	# of firms
sigma=0.10				
Education	$10.1	$9.0	-12.2%	35
Hospitals	$5.3	$4.7	-12.7%	15
Hotels	$6.5	$6.8	5.8%	38
Merchandise	$1.5	$1.9	21.0%	17
Grocery	$1.3	$1.8	27.7%	17
sigma=0.20				
Education	$10.1	$7.9	-27.8%	35
Hospitals	$ 5.3	$4.0	-32.5%	15
Hotels	$6.5	$5.9	-10.1%	38
Merchandise	$1.5	$1.7	11.7%	17
Grocery	$1.3	$1.7	23.5%	17

Note: The table above presents the bill change when customers are price elastic. Simulated values (demand) come from the model presented in section 4. The sample used for this table are customers who are categorized as rate P. Moreover, the sample period is September of 2014, when system lambda is at its lowest of 2014. System lambda are obtained from FERC.

Table 3.6: Decomposition of the Changes in Bills when Customers are Price Elastic and face zero demand charge (September Bills)

	Average Change in Bills after RTP	Price Level Effect	Price Variation Effect	Fixed Charge
sigma=0.10				
Education	$-27,513.9	$-10,251.8	$-2,062.2	$39,827.01
Hospitals	$ -20,946.2	$ -15,632.5	$-3,248.4	$39,827.01
Hotels	$20,910.3	$-11,589.5	$-7,328.4	$39,827.01
Merchandise	$26,847.0	$-10,420.8	$2,560.53	$39,827.01
Grocery	$28,628.0	$-9,624.7	$-1773.0	$39,827.01
sigma=0.20				
Education	$-25,467.1	$-9,256.6	$-3,435	$38,158.24
Hospitals	$-19,036.7	$-11,486.1	$-7,636.6	$38,158.24
Hotels	$22,924.3	$-12,584.0	$-2,650.2	$38,158.24
Merchandise	$28,658.8	$-7,160.7	$-2,340.34	$38,158.24
Grocery	$30,039.6	$-6,510.8	$-1,609.6	$38,158.24

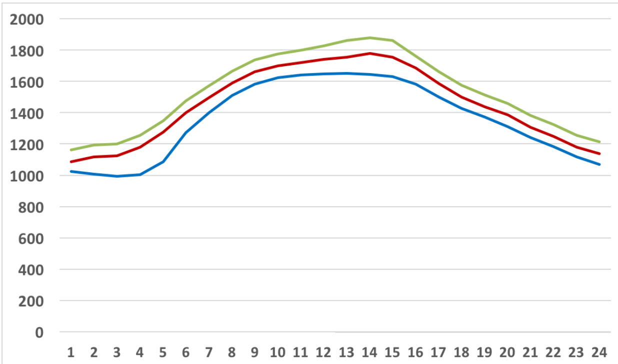
Note: The table above compares bills under RTP and current by sector when customers face a positive demand charge. The first column shows the differences in bills under RTP and current (bills RTP-current). Specifically, negative values indicate that the sector benefits from the new pricing scheme in the form of lowered bills. The second, third and fourth column indicate the price level effect, price variation effect, and fixed effect, respectively.

Table 3.7: Decomposition of the Changes in Bills when Customers are Price Elastic and face positive Demand Charge (September Bills)

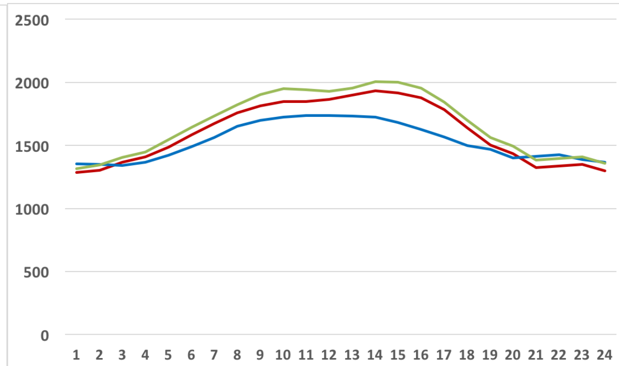
	Average Change in Bills after RTP	Price Level Effect	Price Variation Effect	Fixed Charge
sigma=0.10				
Education	$ -35,490.5	$ -52,178.1	$-5,334.0	$22,021.86
Hospitals	$ -26,906.0	$-42,082.0	$-6,344.3	$22,021.86
Hotels	$ 9,854.1	$-10,005.3	$-2,162.6	$ 22,021.86
Merchandise	$10,948.7	$-9,474.0	$-1,605.8	$22,021.86
Grocery	$11,149.17	$-9,491.2	$-1,381.5	$22,021.86
sigma=0.20				
Education	$-31,053.4	$-45,108.3	$-5,978.8	$20,033.70
Hospitals	$-26,067.0	$-39,193.1	$-7,008.5	$20,033.70
Hotels	$12,516	$-4,300.4	$-3,217.0	$20,033.70
Merchandise	$13,001.4	$-5,002.8	$-2,031.3	$ 20,033.70
Grocery	$14,169	$-4,094.7	$-1,770.2	$20,033.70

Note: The table above compares bills under RTP and current by sector when customers face zero demand charge. The first column shows the differences in bills under RTP and current (bills RTP-current). Specifically, negative values indicate that the sector benefits from the new pricing scheme in the form of lowered bills. The second, third and fourth column indicate the price level effect, price variation effect, and fixed effect, respectively.

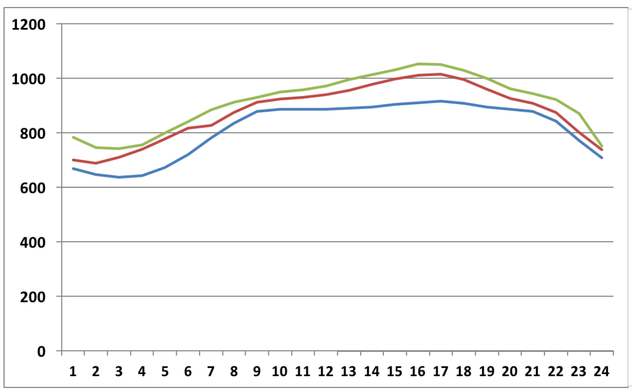
Figure 3.5: Load Profiles under RTP when customers are price elastic with and without Demand Charge (March Bills)



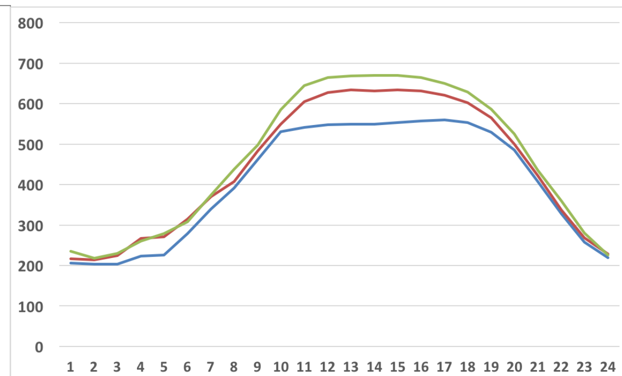
(a) Education



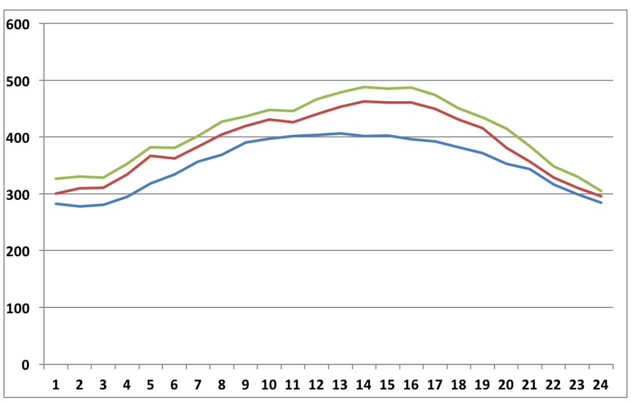
(b) Hospitals



(c) Hotels



(d) General Merchandise



(e) Grocery

Note: Figure (a) through (e) above illustrates the overlay of actual load (blue), simulated load without demand charge (green), and simulated load with demand charge (red) for each sector. When creating these figures, customers with PV are omitted, and created based on September 2014 data. Each load profile is created by simulating the load for each customer and simply taking the average per sector. Data are retrieved from FERC and HECO.

3.7.2 Results for Scenario 2: Price Inelastic Case

Here we present the results for both cases: 1) when customers are price inelastic and face positive demand charge; and 2) when customers are price inelastic and face zero demand charge. Results are presented in table 3.8. Table 3.8 utilizes actual data from September 2014 to calculate the average change in prices under RTP. The fixed charge portion of the bill differ between the two cases because the fixed charge is calculated as $BC_{vo}l$-BR_{vol}+BC_{dc} for the case with positive demand charge and $BC_{vo}l$-BR_{vol} for the case under zero demand charge. We break down the change in bills under RTP into three portions, the price level effect, price variation effect, and the fixed charge. The price level effect measures the change in bills due to a decrease in system lambda. Based on the information in table 3.8, we can see that the price level effect is negative for all sectors, meaning that bills decreased under RTP because system lambda is lower than the effective rates (see figure 3.3).

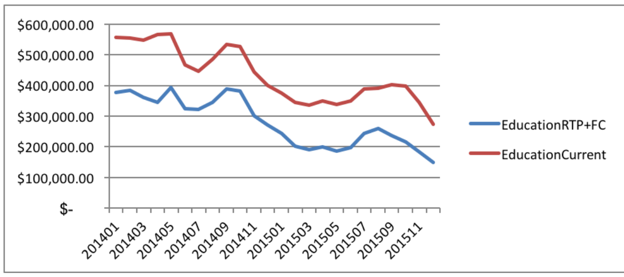
Because tables 3.2 to 5 do not show whether the decrease or increase in bills after RTP is due to a decrease in price (because system lambda is lower than effective rates) or to the magnitude of the fixed charge, table 3,8 also provides the decomposition of the change in bills. The results in this table show that customers who benefit from RTP are again the education and medical sectors. However, the average change decrease in bills tends to diminish in the case where demand charge is equal positive because the demand charge is added on to the volumetric portion of the RTP payment. For all sectors regardless of demand charge, the price level effect is negative because customers face a lower rate per kilowatt hour under RTP. Furthermore, consistent with table 3.5 that illustrates the percent change in bills for the price elastic case and zero demand charge, the accommodation sector benefits from RTP when demand charge is zero, but the benefits disappear when the demand charge is positive. Hence, the accommodation can benefit from RTP that consists of no demand charge. Moreover, hotels only face a slightly higher RTP bill when demand charge is positive, indicating that depending on the value of the fixed charge, the accommodation sector may benefit from RTP under the inelastic case. Consistent with the previous tables, the losers from RTP are the department and grocery sectors, with bills under RTP being higher in both zero and positive demand charge cases.

The third column shows the price variation effect which represents the change in bill that arises from the changes in hourly system lambda. Again the price variation effect is negative for all sectors. Finally, the last column in table 5 indicates the fixed charge portion of the bill under RTP. This value is calculated using the method presented above under "case 2 when demand charge is positive." The fixed charge is lower when demand charge is positive due to the way fixed cost calculation is set. We can conclude from table 3.8 that customers in all sectors indeed benefit from a lower volumetric rate under RTP but winners and losers arise when the price level effect is not large enough to cancel the fixed costs. Moreover, the addition of a demand charge to the RTP structure plays a role in whether a customer benefits from RTP or not. Sectors such as accommodation tend to benefit under the case where demand charge is equal to zero, but not when a demand charge is incorporated in the RTP structure.

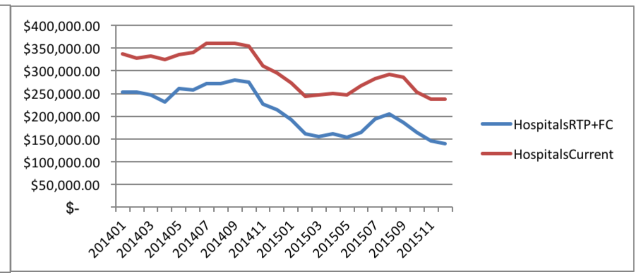
Table 3.8 only presents simulations for September so we present how RTP and current bills change over time. The results are presented in figure 3.6 and includes the case where demand charge is zero. Figure 3.6 shows the changes in bills under an alternative pricing structure relative to existing flat rate structures for every year month combination. The monthly current bills presented in this table are calculated by multiplying the sum of the 15-minute interval data by month and multiplying it by the effective rate, then adding the demand charge. The monthly current bill is calculated using actual values from the data. On the other hand, the monthly alternative bill is calculated as system lambda multipled by the 15-minute kWh. Hourly system lambda is interpolated linearly to match the consumption data. This table shows how customer bills change when customers face positive demand charge. As seen from the figure, some customer bills increase compared to the flat rates. Grocery stores are the losers from a dynamic rate structure than a flat rate one in this scenario. The figure indicates that, on average, grocery stores face a 35,000 dollar increase in bills over the years 2014 to 2015, with the difference between current and alternative bills being larger in 2014 than in 2015. This could be the case because both effective rates and system lambda significantly decrease from October 2014 to Mid 2015 (see figure 3.1), but system lambda decreases more on the margin compared to the effective rates. This can also explain why bills under dynamic pricing is less than that of the current bill using the same kWh consumption level for the merchandising sector. Specifically, bills under current pricing is lower than that of alternative rates in 2015, but vice versa in 2015 for the merchandising sector. Finally, the accommodation sector has minor benefits from the alternative pricing structure relative to flat rate pricing, although they have load profiles that are align with that of the systems (figure 3.2 (c)).

Based on our findings winners from alternative rate structures are the educational and medical sectors. These findings are align with simulation results presented in Borenstein's paper on wealth transfers under RTP (2005). Borenstein finds that winners of RTP on average are significantly larger customers. Moreover, his study finds that the average electricity consumption by firms that would see their bills decrease from time-of-use to RTP is about twice as great as the average electricity consumption by firms that would see their bills increase under alternative rates. Figure 3.1 shows the load share by C&I sector, and you can observe that the winners under the alternative pricing structure are the sectors that have a high load share such as the education, hotels, and medical sectors. Table 3.1 provides summary statistics for each sector. Energy consumption and demand from 2014 are reported in this table. As seen from the table, sectors who have a large share load have the highest peak demand. Its important to note that the magnitude of bill decreases under the alternative rates depend not only on load share but also the sector load profile. For example, winners of alternative rate structures have mid-day peaks and does not align with the system peak. This could explain why the accommodation sector has less benefits in terms of bill decreases than the education or medical sector. The accommodation sector has a large load share but has peak loads that are in line with that of the system. Moreover, the merchandising sector has a load profile that has a high peak in the daytime when the system profile is relatively. Intuitively, it can be the case that the merchandising sector could be the winners of an alternative pricing structure. However, their load share is a small portion of the total sector shares.

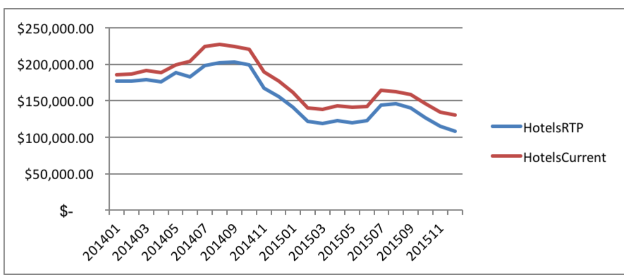
Figure 3.6: monthly bill changes over time (2014-2015): Current versus alternative rates when customers are price Inelastic and face zero demand charge



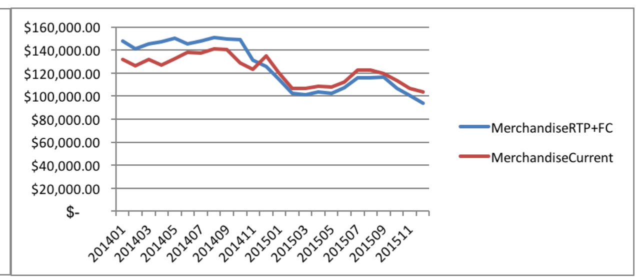
(a) Education



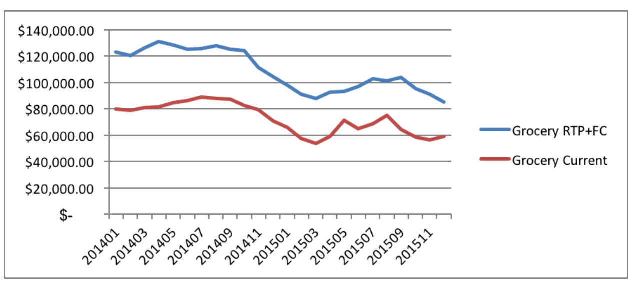
(b) Hospitals



(c) Hotels



(d) General Merchandise



(e) Grocery

Note: Figure (a) through (e) above illustrates the changes in bill under current and alternative rates for all sectors given that customers are price inelastic. The red line indicates the value of bills for the year month combination, while the blue line indicates the bills under the alternative rates. The fixed charge portion of the alternative bill is calculated as the demand charge portion of the bill plus the volumetric rate subtracted by the volumetric portion under alternative rates. We then divide this number by the number of customers in out sample, which is about 119. The own price elasticity used in this simulation is 0.1

Table 3.8: Change in Bills when Customers are Price Inelastic: Two Cases when Demand Charge is zero and positive (September Bills)

	Average Change in Bills after RTP	Price Level Effect	Price Variation Effect	Fixed Charge
$DC = 0$				
Education	$-66,463.2	$-109,020.9	$-3,928.3	$46,486.0
Hospitals	$-72,418.3	$-114,590.2	$-4,314.1	$ 46,486.0
Hotels	$-16,051.7	$-60,242.1	$-2,295.6	$ 46,486.0
Merchandise	$11,861.0	$-33,512.4	$1,112.6	$ 46,486.0
Grocery	$18,446.4	$-27,029.9	$-1,009.7	$ 46,486.09
$DC > 0$				
Education	$-8,041.8	$-23,882.9	$-2,901.7	$ 18,742.8
Hospitals	$ -14,134.3	$-29,612.2	$-3,246.8	$ 18,742.8
Hotels	$113.05	$-16,859.1	$-1,750.6	$ 18,742.8
Merchandise	$15,354.8	$-2,573.2	$-814.7	$ 18,742.8
Grocery	$11,824.6	$-6,186.2	$-731.9	$ 18,742.8

Note: The table above compares bills under RTP and current by sector when customers face a positive demand charge. The first column shows the differences in bills under RTP and current (bills RTP-current). Specifically, negative values indicate that the sector benefits from the new pricing scheme in the form of lowered bills. The second, third and fourth column indicate the price level effect, price variation effect, and fixed effect, respectively. The own price elasticity used in this case is 0.1.

3.8 Conclusion and Discussion

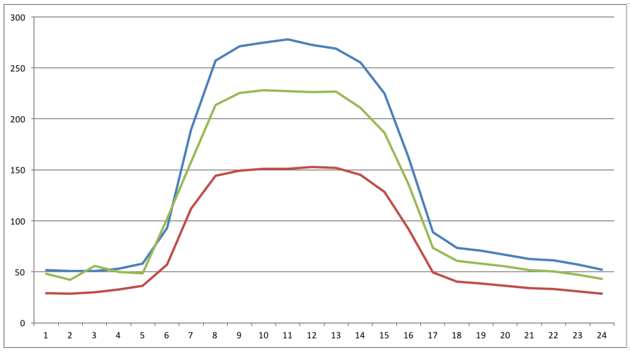
Researchers have theoretically and empirically showed the benefits of dynamic pricing schemes such as RTP in the residential sector. However, studies on the impact of dynamic pricing schemes on sectors within the C&I sector has been sparse, when C&I customers account for two-thirds of electricity loads (Hawaiian Electric Company 2015). Utilizing electricity consumption data for C&I sectors from Hawaiian Electric Company, we estimate the potential bill losses and gains under current and alternative rate structures given two scenarios with varying elasticities. We introduce a novel simulation model of customer electricity consumption to generate demand when customers are price responsive. The simulation model tries to generate energy consumption values that align with our theory. Findings from the simulations correlate with that of Borenstein (2005) and show that introducing a dynamic pricing structure can harm some customers depending on the load shape of the sector and their load share. Sectors that have peaks that do not align with the system and have a large load share, such as hospitals and education, benefit the most from dynamic pricing schemes in both elastic and inelastic scenarios. This study can inform policy makers of the winners and losers if RTP were to be adopted and serve as a guide towards efficient pricing in Hawaii.

Future research includes calculation of consumer surplus when customers face a billing regime that resembles a dynamic one. Although we find that there are no losers under dynamic pricing when consumers are price responsive, the simulation can generate bias results. A paper by Borenstein not only calculates the total payments for customers, but also consumer surplus because "total payments fail to capture the benefits to consumers when they increase consumption during low-price hours and would misstate the losses when a customer reduces its bill by lowering consumption during high price periods, but also loses the value of that consumption (Borenstein, 2007)."

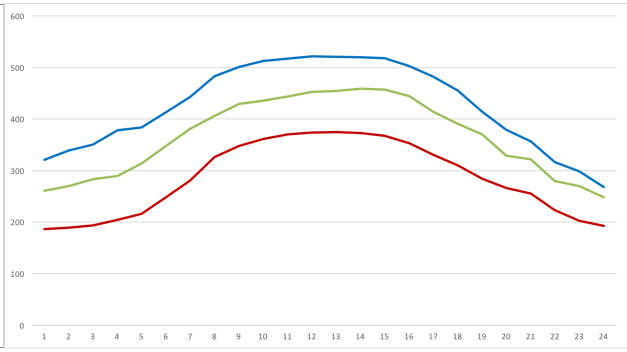
Another possibility for future research is allowing the fixed charge to vary by firm or sector. When considering an alternative pricing structure such as RTP, it is more realistic to allocate varying fixed costs by customer. As a second analysis, we can calculate the total bill under RTP by allocating fixed costs using a method similar to (Galetovic, Muñoz, & Wolak, 2015), who allocates fixed costs based on a fixed capacity payment and capacity of each firm. The capacity payment equals the cost of investing in a generator that runs during the system peak periods.

Appendix B

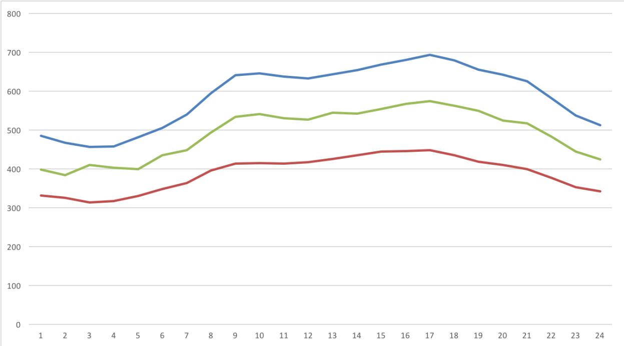
Figure 3.7: Load under Alternative Rates: Two cases when customers are price elastic and face positive or zero demand charge



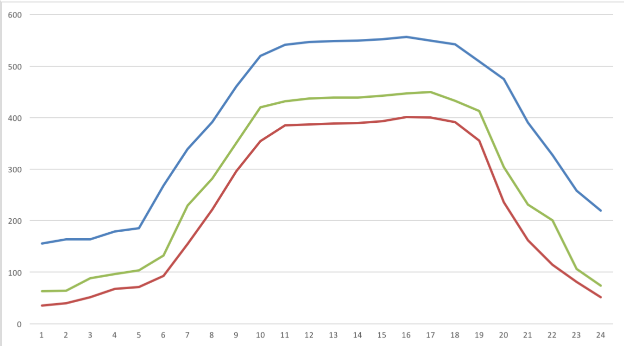
(a) Education



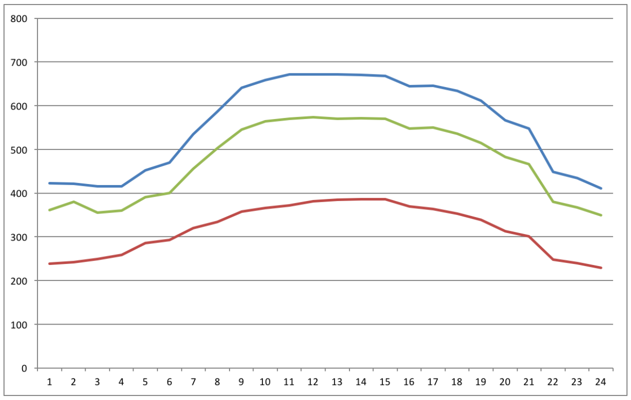
(b) Hospitals



(c) Hotels



(d) General Merchandise



(e) Grocery

Note: The red line in the figure represents the load profile for each sector under alternative rates and no demand charge. The blue line illustrates the load for the case when customers are price elastic and face a positive demand charge. It is important to note that these are load profiles for one customer taken from each sector and is not an average. Load profiles are created using the simulated values.

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