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Abstract:

In this Dissertation, three independent studies analyze the impact of recent changes in both supply and demand sides of the U.S. electricity sector. Below is a brief description of three essays.

I. Coal Plant's Response to Renewable Portfolio Standards

Renewable Portfolio standards require load-serving entities to purchase a given percentage of their electricity sales from eligible renewable energy technologies. This study analyzes the impact of RPS on the coal utilization by coal plants of Pennsylvania, New Jersey, and Maryland (PJM) electricity market. We develop a panel dataset of 259 unique PJM coal-fired utility plants' integrating their fuel purchases with state-level RPS energy mandates, electricity prices, and fuel prices from 2001 to 2011, covering both pre-RPS and post-RPS era. Since selection of RPS policies may be non-random, we employ a two-step Heckit model to control for states' decision to adopt an RPS and choose yearly RPS levels. The results show that a percentage point increase in state's yearly energy target increases the average plant's coal purchase by 45 thousand tons. These results are approximately consistent across selection-corrected models. The analysis showing the positive impact of RPS yearly targets on PJM coal plants' coal purchases suggests a few things. There are fewer coal plants operating at the margin. Moreover, RPS yearly energy targets are fairly low at present; they are scheduled to increase considerably in coming years. Renewable Portfolio Standards may decrease the amount of fuel utilized by coal plants when RPS mandates increase in future.

II. Residential Customers Response to Critical Peak Events of Electricity: Green Mountain Power Experience

Demand response (DR) programs, usually through peak pricing and incentive-based approaches, can encourage customers to reduce or shift consumption during peak periods. This benefits utilities by lowering short-run generation costs and reducing the need for some long-run peak-driven investments. This paper analyzes the impact of Vermont's Green Mountain Power's (GMP) emergency DR programs on residential customers' electricity consumption during a two-year pilot study program in 2012–2013. The 3,735 single-home residents of Central Vermont area were separated into six treatment groups and two control groups resulting into 26 million hourly load observations during the period of the study. Our analysis shows that incentive-based demand response programs have statistically significant impacts on reducing peak load. Specifically, CPR rates reduced peak load usage 6% to 7.7% and CPP rates reduced peak load between 6.8% and 10.3% during critical peak events. Moreover, on average, IHD-equipped participants' monthly energy consumption was 2.0% to 5.3% lower than the monthly energy usage of non-IHD customers. However, none of the CP rate and IHD treatments induced a persistent response across multiple critical events and none of the treatment groups exhibited a consistent response to critical peak events. Based on our evaluation of GMP's DR programs during 2012 and 2013, neither critical peak pricing nor rebates are themselves sufficient to substitute for new capacity to meet resource adequacy requirements.

III. Analysis of Load and Price patterns in the U.S. Electricity Sector

The study analyzes hourly electricity loads and marginal costs of electric entities with of extreme value theory (EVT), a concept widely used in the financial sector. For each year's hourly data of balancing authorities and utilities, we fit generalized extreme value (GEV) distribution and estimate the parameters of the distribution with an aim of comparing how these parameters have changed over time and market regions. We also account for the time dependencies, seasonalities, and near-time clustering present in the electricity markets – both for electricity load and prices – with the help of autoregressive conditional hetereskedastic models. The results show that the distributions of hourly load and lambda values are fat tailed. Hourly lambda values have more extreme values generating fatter tails than hourly electricity load. We also show that extreme tail quantiles estimated with the GEV parameters at different percentile levels are comparable with the percentiles of actual observations.

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Chapter 1: Introduction

The United States electricity sector has gone massive changes over the last few decades. The deregulation of electricity in most of the US regions, new renewable energy policies and subsidies, and implication of global warming has not only affected the demand and supply sides of the electricity sector, but also raised the issue of the reliability and adequacy (Mansur, 2008; Chandler, 2009; Lyon and Yin, 2010; FERC, 2012).

Some of the heavily affected areas with the new policies and market changes are coal-fired power plants and utility sectors. The supply of coal-fired electricity has decreased 50% to 37% from 2002 to 2012[1] (EIA, 2013). Similarly, the increase in electricity demand during the peak period has increased the reliability cost to the utilities (Spees, 2008; Faruqui et. al, 2010). There is a need to develop rigorous mechanism in order to analyze the impact of the recent changes by carefully acknowledging the specific details of each affected sector. In this proposal, three independent studies analyze the impact of recent changes in both supply and demand sides of the U.S. electricity sector.

The first paper studies the effect of Renewable Portfolio Standards on coal plants' fuel purchase decisions. Renewable Portfolio Standards (RPS) require load-serving entities to purchase a given percentage of their electricity sales from eligible renewable energy technologies. With the help of state-level RPS energy mandates, electricity prices, and fuel prices information, we analyze annual coal purchases decisions of Pennsylvania, New Jersey, and Maryland (PJM) region's 259 coal-fired plants. Since the selection of RPS policies may be non-

[1] At the same time interval, natural gas share in electricity generation jumped from 17.9 percent to 24.7 percent and share of renewable generation, excluding conventional hydroelectric, doubled from 2 percent to 4.7 percent (EIA, 2012). In 2012, natural gas provided 30 % of the electricity, whereas 19% of the electricity came from nuclear plants, 7 % from hydropower, and 5 % from other renewables (EIA, 2013).

random, we employ a two-step Heckit model to control for states' choice to adopt an RPS and the level of the RPS in each year.

The results show that a percentage point increase in state's yearly energy target increases the average plant's coal purchase by 45 thousand tons. These results are approximately consistent across selection-corrected models. The analysis showing the positive impact of RPS yearly targets on PJM coal plants' coal purchases suggests a few things. There are fewer coal plants operating at the margin. Moreover, RPS yearly energy targets are fairly low at present; they are scheduled to increase considerably in coming years. Renewable Portfolio Standards may decrease the amount of fuel utilized by coal plants when RPS mandates increase in future.

The second paper analyzes the impact of Green Mountain Power (GMP) launched emergency DR programs on the electricity consumption behaviors of residential customers of Rutland, VT during a two-year pilot study program in 2012-2013. During critical peak events, customers either face high price or get incentives for reducing electricity lower than their baseline. We create a panel dataset combining hourly electricity load, critical peak event information, weather variables, and participant specific characteristics. The 3735 single-home residents of Rutland area are separated into six treatment groups and two control groups resulting into 26 million hourly load observations during the period of the study.

Our analysis shows that incentive-based demand response programs have statistically significant impacts on reducing peak load. Specifically, CPR rates reduced peak load usage 6% to 7.7% and CPP rates reduced peak load between 6.8% and 10.3% during critical peak events. Moreover, on average, IHD-equipped participants' monthly energy consumption was 2.0% to 5.3% lower than the monthly energy usage of non-IHD customers. However, none of the CP rate and IHD treatments induced a persistent response across multiple critical events and none of the treatment groups exhibited a consistent response to critical peak events. Based on our evaluation of GMP's DR programs during 2012 and 2013, neither critical peak pricing nor rebates are themselves sufficient to substitute for new capacity to meet resource adequacy requirements.

Finally, the third paper analyzes the peak demand and high electricity prices of electric providers and balancing authorities of United States with the help of extreme value theory, a concept widely used in the financial sector. We fit generalized extreme value distribution to the peak load and electricity price in order to predict the parameters of the distribution and analyze how these parameters change over time and across geographic locations. The predicted parameters allow comparing the usage of generation capacities over the years and also across different electric entities and balancing authorities. We also account for the time dependencies, seasonalities, and near-time clustering present in the electricity markets – both for electricity load and prices – with the help of autoregressive conditional hetereoskedastic models.

The results demonstrate that the distributions of hourly load and lambda values are fat tailed. Hourly lambda values have more extreme values generating fatter tails than hourly electricity load. This is understandable because hourly load has upper limit due to physical constraints such as transmission lines and generation capacity. We also estimate extreme tail quantiles with the help of generalized extreme value parameters. The results show that extreme tail quantiles estimated with the GEV parameters at different percentile levels are comparable with the percentiles of actual observations.

Chapter 2: Coal Plants' Response to Renewable Portfolio Standards

Abstract

Renewable Portfolio standards require load-serving entities to purchase a given percentage of their electricity sales from eligible renewable energy technologies. This study analyzes the impact of RPS on the coal utilization by coal plants of Pennsylvania, New Jersey, and Maryland (PJM) electricity market. We develop panel dataset of 259 unique PJM coal-fired utility plants' fuel purchases from 2001 to 2011, covering both pre-RPS and post-RPS era, integrating with state-level RPS energy mandates, electricity prices, and fuel prices. Since selection of RPS policies may be non-random, we employ a two-step Heckit model to control for states' choice to adopt an RPS and the level of the RPS in each year. The results show that a percentage point increase in state's yearly energy target increases the average plant's coal purchase by 45 thousand tons. These results are approximately consistent across selection-corrected models. The analysis showing the positive impact of RPS yearly targets on PJM coal plants' coal purchases suggests a few things. There are fewer coal plants operating at the margin. Moreover, RPS yearly energy targets are fairly low at present; they are scheduled to increase considerably in coming years. Renewable Portfolio Standards may decrease the amount of fuel utilized by coal plants when RPS mandates increase in future.

1. **Introduction**

How do coal plants respond to Renewable Portfolio Standards (RPS)? Renewable Portfolio standards require load-serving entities to purchase a given percentage of their electricity sales from eligible renewable energy technologies. While RPS do not nominally affect fossil-fired generators, some incidence of these policies almost certainly fall on them. As annual RPS energy targets rise, low marginal cost renewable generation increases and may effectively shift the electricity supply curve. In turn, this shift may displace some coal-fired electricity generation. Moreover, renewable energy subsidies act to reduce the wholesale electricity price. At the same time, RPS treats fossil fired generation from different fuel types equally. On average coal-fired generators produce twice amount of carbon dioxide than natural gas plants to generate same amount of electricity (EIA, 2012), thus it is important that the RPS has an impact in reducing electricity generation from coal-fired generators. It is not clear at present whether RPS succeeds in this respect. This study analyzes the impact of RPS on the coal utilization by coal plants of Pennsylvania, New Jersey, and Maryland (PJM) electricity market.

Previous papers study the impact of regulations on coal industry from two different approaches. The first group of papers use transaction cost theory to look at the changes in coal contracts and quantity purchased. Joskow (1987) introduces transaction cost theory of specific relationship investments to analyze the contract purchases between mining companies and coal plants. Palmer et al. (1993) conclude that developments of technological factors, market characteristics, and regulatory changes increase the flexibility of fuel supply arrangements. Koshnik and Lange (2011) analyze the probability of renegotiating coal contracts due to the policy shock of 1990 Clean Air Act Amendments. The second group of literature considers production constraints of the coal-fired plants to look at the impact of regulations in electricity generation. Mansur (2008) measure the change in social welfare due to electricity restructuring in the PJM market. Similarly, Cullen (2011) use dynamics of power plants such as intertemporal constraints and power markets to quantify the emissions offset by the increase in wind electricity in Texas.

The purpose of this study is therefore to analyze the relationship between RPS and coal plant fuel utilization. We focus on the PJM market and develop a panel dataset that integrates information on coal plant characteristics and fuel purchases, state-level RPS energy mandates, electricity prices, and fuel prices. The final dataset consists of annual level observations of 259 unique coal plants in PJM states from 2002 to 2011. Since the selection of RPS policies may be non-random as it is state's decision to implement the mandate, we employ a three-step Heckit model to control for states' choice to adopt an RPS and decide the annual RPS target level. We use a contagion model to identify the first stage selection, where we hypothesize that a state's decision to adopt RPS depends on the "neighboring" states RPS status, its renewable potential, generation shares, and socio-economic variables. We then use the selection-corrected estimates of RPS levels to quantify the impact of RPS on coal utilization by plants.

To our knowledge, no prior studies look at the influence of state-level RPS policy on the amount of coal used for power generation. Coal-fired power plants have relation-specific investment characteristics and, as well as, distinct production constraints. In this paper, I develop a theoretical model by combining both of these aspects of coal power plants. This paper helps understand how state-level RPS policy is affecting coal generation and provides insights on coal plants' response to the renewable policy. The study, in the long run, may help formulate energy policy to ensure greenhouse gas reductions from the US electricity sector. The paper also contributes to the RPS literature by developing Heckit model to address the sample selection associated with the adoption and design of state-level RPS policy.

The base model, Ordinary Least Squares (OLS) with plant fixed effects, shows that one percentage point increase in state's yearly energy target increases the average plant's coal purchase by 42 thousand tons. These results are approximately consistent across selection-corrected models. The analysis showing the positive impact of RPS yearly targets on PJM coal plants' coal purchases suggest few things. There are fewer coal plants operating at the margin, thus RPS do not impact the way we hypothesized. Moreover, RPS yearly energy targets are fairly low at present; they are scheduled to increase considerably in coming years. RPS may decrease the amount of fuel utilized by coal plants when RPS mandates increase in future.

The rest of the paper follows with the brief description on coal-fired plants, fuel procurement methods, RPS policy, and PJM market in section 2. A review of relevant literature is discussed in section 3. In section 4, the paper develops the theoretical model. The econometric method is discussed in section 5. The complete data description is provided in Section 6. Section 7 contains descriptive statistics followed with discussion of regression results in section 8. Section 9 concludes the paper and talks about future research ideas.

2. **Background**

The electricity sector consumed 93% of the total coal consumed in the US in 2011[2] (EIA, Short Term Energy Outlook). Even though the share of coal fired generation in the US electricity sector has declined from 50% to 37% from 2002 to 2012[3] (EIA, 2013), coal remains to be one of the dominant sources of electricity generation in the US for future. It is mainly for the three reasons – the price of coal is fairly consistent, coal mines are widely distributed, and existing infrastructures, such as transportation and power plants, have long lives.

Coal plants are a major source of carbon emissions in the US electricity sector and play a role in U.S. economy. In 2011, utility coal plants in the United States produced a total of 1.7 billion tons of carbon emissions, 75% of total emitted from the electricity sector (EIA, 2012). With the absence of carbon policy[4] in the US, the closest policies that work in favor of reducing carbon emissions are the regulations aimed at promoting renewable generation. One of such renewable policies is state-level RPS. Even though RPS yearly energy targets are fairly low at

[2] In 2011, the total consumption of coal was 999.1 million short tons, out of which electric power sector used 928.6 million short tons of the coal. Retail and general industry used 49.1 million short tons, whereas coke plants consumed 21.4 short tons (*Short-Term Energy Outlook*, EIA, September 2012).

[3] At the same time interval, natural gas share in electricity generation jumped from 17.9 percent to 24.7 percent and share of renewable generation, excluding conventional hydroelectric, doubled from 2 percent to 4.7 percent (EIA, 2012). In 2012, natural gas provided 30 % of the electricity, whereas 19% of the electricity came from nuclear plants, 7 % from hydropower, and 5 % from other renewables (EIA, 2013).

[4] Except RGGI and California's new carbon policy. The Regional Greenhouse Gas Initiative (RGGI) is a market-based cap-and-trade policy in 10 ten northeast and Mid-Atlantic States of US. It is established with an aim of reducing emissions of CO_2 and targeted to the fossil fuel-fired plants with capacity of at least 25 MW. From 2009 to 2014, the emissions cap is kept constant at 188 million short tons per year and then reducing by 2.5 percent each year starting from 2015 to 2018.

present, they are scheduled to increase considerably in coming years. In the PJM region, the final RPS targets of Illinois and New Jersey are going to be 21% and 19%, respectively, of their total electricity sales by 2025. We expect the demand of fossil-fired electricity to decrease with the increase in RPS mandates.

2.1 Coal-fired Power Plants

Coal-fired power plants are designed for a specific type of the coal considering attributes such as calorific value, amount of moisture, and ash content. The coal specific characteristics affect the plant's heat rate, its generating efficiency, and ultimately the marginal cost of the electricity. Coal rank varies significantly according to the mining location and carbon content (Future of Coal, 2007). Transportation cost, mining location, cleaning costs, and coal quality affect the decision of choosing the site of the power plant. The design of coal-fired generators according to the coal attributes introduces relationship-specific investment behavior that affects the plant's fuel procurement policy. Section 3 discusses more about the relation-specific investment behavior of the coal industry.

Similarly, the electricity produced from the coal plant depends on the technologically induced production constraints, operating efficiency, pollution controls, and cost of electricity. Coal plant specific characteristics, collectively known as intertemporal constraints, limit the ability to change the amount of electricity produced at any time and affect the firm's production cost function. If a plant is shut down, it incurs start-up costs to resume its operation. Ramp rate determines how fast a power generator can change output. Similarly, minimum load and minimum run time also incur additional costs and affect the cost of operation. There is a tradeoff between start-up and marginal costs of the coal-fired utility when making a shutdown decision

(Mansur, 2008). Coal plants are traditionally employed as base load plants due to their limited ability to respond to change in electricity demand.

2.2 Fuel Procurement Methods

Coal transactions take place through either long-term contract agreements or spot market purchase. Firms participating in the spot market buy coal at the market price. Contract agreements between a mine and coal-fired plants contain both price and non-price conditions such as price adjustments and options of renegotiation for the ex-post change in the market (Koshnik and Lange, 2011). Long-term contract vary in price provisions. For example the contract can be fixed, base price with increase depending on market conditions. The contract can be periodic or conditional on renegotiation (Palmer, 1993). The average length of coal contracts signed between 1979 and 1999 was 4.4 years (Koshnik and Lange, 2011).

There are risks associated with both contract-based purchases and spot market transactions. Contracts limit adjustment of purchase agreements as the market conditions change. Similarly, price volatility in the spot markets means that substantial uncertainties characterize spot purchases. Thus, coal-fired plants usually choose a combination of both long term contracts and spot market purchases in its fuel procurement policy. Moreover, the type of the transaction that a firm chooses also depends on the coal attributes, coal-plant type, and the structure of the coal plants.

2.3 Renewable Portfolio Standards

The Renewable portfolio standards (RPS) is a state-level policy that requires utility companies to include a minimum amount of electricity from eligible renewable technologies. The Database of State Incentives for Renewable Energy (DSIRE) lists nine types of different renewable technologies – wind, concentrated solar power, distributed photovoltaic, centralized photovoltaic, biomass, hydropower, geothermal, landfill gas, and ocean (DSIRE, 2011). The total state-level RPS mandates covered 50% of the country's total electric load in 2010. The main goals of RPS are to increase diversity in the electricity portfolio with the help of sustainable energy resources and reduce greenhouse gas emissions. It is implemented through an output-based subsidy to give a continuous benefit for renewable producers, commonly by issuing Renewable Energy Certificates (REC).

The REC credits serve as a proof of electricity produced from eligible renewable technology. Generally, one REC credit refers to 1MWh of electricity produced from a renewable source. These RPS policies vary significantly across states. However, in some states, certain types of renewable technologies are given more preference than others for the same amount of electricity generated. For example, Delaware provides 3.5 REC credits for each MWh of electricity produced using wind energy and 3 credits per MWh from distributed photovoltaic, whereas it provides only 1 credit if generated from centralized photovoltaic, biomass, and other renewable sources (DSIRE, 2011).

The scope and characteristics of RPS vary tremendously among states – mainly in structure, size, eligibility, and administrations (Wiser et al, 2007). The Union of Concerned Scientists (UCS) has categorized differences of RPS policies among states in thirty-four unique categories. Some of the main areas are renewable energy target percentage, eligible renewable technologies, obligated electric entities, geographical entities, and subsidies (UCS, 2011). States have different target goals and yearly requirements. Moreover, the starting and ending dates for the RPS vary.

This study uses yearly RPS energy targets[5] expressed in terms of percentage of state's total electricity sales as a measure of the state-level RPS policy. The eligible renewable sources may be further subcategorized into different tiers with the objective of promoting specific type of renewable sources. Thus, tiers consist of target goals that need to be met by using only the types of renewable technologies that are specified in each tier (DSIRE, 2011).

2.4 PJM Market

The PJM Interconnection is a regional transmission organization (RTO) that operates a competitive wholesale electricity market in all or parts of thirteen US states[6]. It balances electricity demand and supply by continuously monitoring energy market to obtain transmission reliability. The market uses locational marginal price (LMP) to account for the transmission congestion and promote efficient use of the transmission system. The PJM energy market consists of day-ahead and real-time markets. Day-ahead market finalizes hourly LMP a day in advance based on "generation offers, demand bids, and scheduled bilateral transaction" (PJM Market Fact Sheet, 2012). Real-time market uses LMPs calculated at five-minute intervals based on the operating condition and transmission.

Among fourteen PJM states, seven have mandatory annual RPS policy in effect by 2011. Even though mandatory RPS policy in North Carolina and Michigan started in 2012, the study considers them to be non-RPS states since the study is limited to year 2011. Three states,

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[5] All load-serving entities – investor-owned, power marketers, municipal utilities, and rural cooperatives – operating in a state may not have to meet the RPS requirements. Delaware require all four lead-serving entities to comply with the RPS mandates (DSIRE, 2011). As a result, there is wide variation on what percentage of total electricity sales within a state is mandated by RPS policy (DSIRE, 2011). Thus, yearly targets are adjusted for the load covered by RPS mandates.

[6] PJM serves Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia.

Indiana, Virginia, and West Virginia have voluntary RPS policy. Kentucky and Tennessee have not adopted any sort of RPS policy. The Washington, D.C. area is not included in the study as most of the data are not available.

3. **Literature Review**

The purpose of this research is to quantify the impact of state-level renewable energy policy in the amount of coal used by coal-fired generators. Previous studies have looked at the effect of energy policies in the amount of coal used and the coal-contract duration between the coal plants and mining companies.

Joskow (1987) analyzes the coal contracts between mining company and coal plants using transaction cost theory of specific relationship investments. The theory states that when a buyer and a seller perform a transaction for relation-specific investment, they agree a long-term contract with the maximum quantity possible to avoid repeated bargaining. The paper uses site specificity and physical asset specificity pointed out by Williamson (1979) to analyze the contract transactions between mining companies and electric utilities. Joskow (1987) argues that a plant relies on a particular supplier for the maximum possible amount of coal and the cost of breaching contract increases with increasing reliance in a single supplier. Similarly, a coal mine finds hard to breach a contract if a single plant buys most of its coal through a single contract. Joskow (1987) finds that both buyers and suppliers find advantages in longer-duration “contracts that specify the terms and conditions of repeated transactions ex ante, rather than relying on repeated bargaining”.

Site-specificity occurs in coal supply relationships, as coal has to be transported from coal mining area to generation plants. Some coal-fired plants are built simultaneously with mines in order to reduce transportation costs; these types of plants are referred as ‘mine-mouth.’ Joskow (1987) uses a dummy variable to account for mine-mouth plants. Kozhevnikova and Lange (2009) use distance between coalmines and power plants to account for the impact of geographical proximity between buyer and seller in the quantity of coal.

Similarly, physical asset specificity for a coal plant refers to the dependence on a single contract for fuel procurement process. Coal-fired plants are designed to use a specific type of the coal that has particular heat, sulfur, and range of moisture content. Many design parameters of the plant have to be changed in order to use different type of coal (Palmer, 1993). Joskow (1987) uses dependence of a single coal contract, both for plant and mine, to measure the asset specificity. Specifically, for a coal-plant, it's the percentage of coal acquired from each contract in the plant's total coal utilization. Similarly, for a mine, it is the percentage of its total coal production sold through each contract.

The paper by Kozhevnikova and Lange (2009) measures the effect of energy regulations on contract duration using long-term contracts data. This work is continuation of Joskow's paper, but includes recent data and energy policies from 1979 to 1999 in the model. Three regulatory reforms used in the empirical analysis are Staggers Act of 1980, Clean Air Act Amendments (CAAA) of 1990, and electricity restructuring. Kosnik and Lange (2011) study the factors affecting coal contract renegotiation after the policy shock. The paper assumes that coal contracts renegotiation occurs if the change in the profit due to the policy shocks cannot be balanced by altering the coal characteristics[7] delivery change.

Mansur (2008) incorporates the production constraints of electricity plants of the PJM region that result in non-convex cost function to study the loss in social welfare due to electricity restructuring. With the help of revealed preference argument and ex-post analysis of firm's production behavior, the paper looks at the behavior of cost-minimizing firms in the post-restructuring era.

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[7] Characteristics that Kosnik and Lange (2011) mention are sulfur content, heat content, and coal-mining region.

Cullen (2010) calculates the emission offset of the substituted conventional fossil-fired electricity due to increase in wind power in the electricity grid of Texas. The result finds that wind power plant, not only displaces quick responding natural gas plants, but also the base-load coal-fired plants. The paper concludes that offsetting CO_2 primarily drives renewable policies and environmental benefits are higher than cost incurred (Cullen, 2010). The paper also mentions that RPS is one of the primary subsidies for driving wind power installations across the US.

4. **Theoretical model**

This section develops a theoretical approach to study the changes in coal utilization due to the state-level RPS regulation[8]. Coal plants procure fuel both through long-term contracts and spot markets. Even though coal plants are obliged to honor contract commitments, the flexibility in fuel purchases comes from their decision to participate in the spot market. Coal plants decide to participate in the spot market based on the amount of coal procured through contracts and demand requirements. Moreover, while revising or renegotiating contracts that are signed before the enactment of RPS policy, coal plants of RPS states can adjust their agreements to account the impact of the policy since the annual targets of RPS are pre-specified till the final year. Thus, coal plants have both short and long terms flexibilities to consider the impact of RPS in their fuel procurement processes.

I start with a single and price-taking, coal-fired utility in a competitive electricity market that does not have to comply with the RPS mandate. Let $\boldsymbol{g}$ be the amount of electricity produced by using $\boldsymbol{q}$ amount of coal at a given year. Electricity generation follows from technology, $e^c = g(q(l), k)$, where $q(l)$ is the quantity of coal burned, $\boldsymbol{l}$ is the $L * 1$ vector of coal

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[8] The notation and suggestions for the theoretical model relies on Professor R. Weaver's comments.

characteristics. We assume that there exists only one type of coal feasible for each plant type *k* to burn. Price of coal depends, $\boldsymbol{r}(.)$, $\boldsymbol{l}$.

The objective of a price-taking firm is to maximize its profit with the consideration of set of incentives such as cost minimization, rate of return, and unit commitment. Relationship specific characteristics, production constraints, and regulations are state variables. I assume state variables to be fixed for a given period of time. The choice variable for a coal-fired utility is to choose the amount of coal to burn. Amount of electricity generated from coal-plant is a function of exogenous variables ***w*** such as regulation, temperature (Cullen, 2010), and price of alternative fuels such as natural gas and oil. The quantity of coal burned, ***q***, depends on the amount of electricity produced and coal specific characteristics ***l*** such as heat rate, sulfur content, ash values, and mining region

Next, I include the impact of RPS on coal plant's profit function. Renewable Portfolio standards affect the coal plant in the competitive electricity market in at least two ways. First, since the marginal cost of renewable electricity is lower than that of the coal, increased renewable generation as a result of RPS policy pushes the coal-fired electricity to the right of the electricity supply curve. If the shift is large enough, it might push the marginal coal plants out of the market and force them to decrease production or even shut down.

Second, the subsidies provided to renewable power producers in terms of the REC credits also impact coal plant's profit function. In most of the PJM states where electricity market is deregulated, the obligation to meet RPS requirements falls on the utility companies. For every amount of non-renewable electricity purchased, mandated utility companies have to offset the amount equal to annual RPS energy target by purchasing equivalent REC certificates from the renewable energy producers. The RPS subsidy, in terms of REC credit, acts to depress the wholesale electricity price.

The effect of the decrease in wholesale electricity price on coal plant depends on where it falls in the short run electricity supply curve. If the coal plant's marginal cost is higher than reduced price, the plant will still operate at the full capacity, but its total profit will decrease. However, if the coal plant is operating in the margin and its marginal cost is lower than the suppressed electricity price, it will either reduce the electricity generation or shut down. The decision to shut down depends on the startup cost of the plant and the difference between marginal cost and depressed electricity price. RPS, thus, impact the price received by coal plants for its generated electricity. In response, fossil generators may improve efficiency or otherwise change their output level to maximize profits.

Now, let's include the impact of regulation (RPS). We define w as percentage of electricity supply, e^{c} , that must come from renewable sources. Then, $w\ e^{c}$ equals to the mandated amount of renewable generated electricity. We also define $e\ \Delta s$ to be the price of renewable electricity procured by coal plants. Similarly, the wholesale price of electricity is $\boldsymbol{p}$. Coal generators sell electricity into wholesale electricity markets at market price $p(t)$ or renewable depressed price, $p_c(t) = \delta\, p(t)$.

Then, the variable profits:

$$(1)\quad \pi \equiv p_c(t)(1-w)\ g(q(l),k) + p(t)\ w\ g(q(l),k) - r(l)q(l) - \rho w g(q(l),k\ )$$

and we note that $p_c(t) = \delta_s p(t)$ where δ_s is state effect $0 \leq \delta_s \leq 1$.

Choice problem for the coal-fired utility is to choose the amount of coal to burn. Then, the first order condition, after taking derivative with respect to q , becomes:

Choice problem for the coal-fired utility is to choose the amount of coal to burn. Then, the first order condition, after taking derivative with respect to q , becomes:

(2) $p_c(t)(1-w)\,\frac{\partial g}{\partial q} + p(t)\,w\,\frac{\partial g}{\partial q} - r(l) - \rho w \frac{\partial g}{\partial q} = 0$

⇨ $(p_c(t)(1-w) + p(t)\,w - \rho w)\frac{\partial g}{\partial q} - r(l) = 0$

Rearranging and substituting $p_c(t) = \delta\, p(t)$, we get

⇨ $(p_c - p_c w + p\,w - \rho w)\frac{\partial g}{\partial q} - r(l) = 0$

⇨ $(p_c + p(1 - \rho - \delta)w)\frac{\partial g}{\partial q} - r(l) = 0$

(3) $\lambda\,\frac{\partial g}{\partial q} - r(l) = 0$ *where* $\lambda(.)$ is the effective price for coal generated electricity.

Then, the solution is:

(4) $q^*(l) = q(\lambda(p, w, \delta_s)r; k))$

(5) $e^{c*} = g(q^c(.), k\,)$

(6) $\pi^* = \pi(\lambda(.), r, k)$

Now, the impact of a change in regulated percentage of renewable electricity, w , on $\pi(.)$:

(7) $\frac{\partial \pi^*}{\partial w} = \frac{\partial \pi^*}{\partial \lambda}\frac{\partial \lambda}{\partial w} = \frac{\partial \pi}{\partial \lambda}\,p(1 - \rho - \delta)$

Similarly, effect on electricity supply

(8) $\frac{\partial q^*(l)}{\partial w} = \frac{\partial q^*}{\partial \lambda}\frac{\partial \lambda}{\partial w} = \frac{\partial q^*}{\partial \lambda}\,p(1 - \rho - \delta)$

Note that $\frac{\partial \pi^*}{\partial \lambda} = g^*(.)$

The research interest of this paper is to find the impact of RPS on the quantity of coal used by the coal plant. Equation (8) gives the change in the quantity of coal consumption plant due to the effect of RPS mandates for the coal-plant.

Hypothesis: During the period of the study, 2002 to 2011, Renewable Portfolio yearly mandates reduce the quantity of fuel used by coal-fired utility of PJM region that are on the margin of electricity supply curve.

5. Econometric Model

5.1 Base Model

The paper uses reduced econometric model with plant-specific and time-fixed effects. Equation (9) is the linear ordinary least square regression used in the empirical analysis.

$$(9) \quad q_{it} = \alpha_i + \beta_t + \beta_1 w_{st} + \beta_2 l_{it} + \beta_3 k_{it} + \beta_4 m_{st} + \varepsilon_{it}$$

where, $i, \ s, t$ index coal-fired plants, states, and years respectively. q is the quantity of coal purchased by the power plant; α_i is the plant fixed effects; β_t is year dummy variables; w is RPS yearly energy targets; l represents coal-plant characteristics; k is investment specific characteristics; m represents electricity market and fuel price related variables; and ε_{ist} are error terms. The goal of this paper is to estimate the coefficient β_1, same as the marginal rate of substitution of equation (8). β_1 gives the change in the quantity of coal purchased due to one percentage point change in state-level RPS yearly energy mandate.

The dependent variable, quantity of fuel procured in each year, includes both contract purchases and spot market purchases. For robustness check, the paper also uses the ratio of annual coal purchase to the nameplate capacity of the generators as an alternate dependent variable. Using coal quantity per plant's capacity (thousand tons per MW) is intuitive for two reasons. One, it helps control for the amount of coal purchased by bigger-fired utilities. Two, it also captures the efficiency improvement of coal plants over the years.

Yearly RPS target is calculated by aggregating annual requirements of each tier of the primary RPS type.[9] If a state's RPS yearly mandate is 5 percent of its total electricity sales then RPS variable takes the value of five.

The empirical model uses different variables to account for the relation-specific investment nature of the coal industry. The variable ***k*** includes coal attributes such as average ash values, calorific values, and sulfur content and a dummy variable to account mine-mouth plants. The paper uses plant-specific fixed affects to account for various coal plant related variables such as RPS obligation of the coal plant, state of regulation, and plant's age.

The econometric model controls for electricity and fuel prices. While electricity price may not impact the demand of electricity significantly due to its inelastic nature, it might affect the supply side of the electricity generation – especially renewable generation. Since the average cost of producing electricity from renewables is higher than fossil fuels, increase in electricity price may make renewable generation competitive with coal and gas-fired generators.

The econometric model also includes annual state-level fuel prices charged to electric sector. The paper uses state-level electric sector coal and natural gas prices to control the possible the possible impact of fuel prices to the coal plants. Natural gas prices can affect the quantity of coal used in at least two ways. Lower natural gas prices attract installation of new gas-fired plants. Reduced natural gas prices also provide coal plants owner incentives to install adjacent gas-fired utilities. The owner then can choose among the collocated plants as peaking units depending on the respective fuel prices.

[9] Few states divide RPS into primary, secondary, and tertiary RPS to mandate different types of utilities separately. In PJM region, Illinois has secondary tier RPS (DISRE, 2011).

5.2 Addressing Selection Bias

The RPS yearly target variable (*w*) is observed only if states have implemented RPS policy. In the main data sample, only 20 percent of the observations have non-zero RPS yearly energy target variable. States that rely heavily on fossil based fuels may decide not to adopt RPS policy. Even if these states adopt RPS policy, they may have weak RPS mandates. On the other hand, state with abundant renewable generated electricity in its portfolio may have higher yearly mandates if it chooses to adopt RPS policy. Considering only observations with non-zero RPS yearly targets introduces sample selection problem (Wooldridge, 2010).

The paper uses a three-part Heckit model to address the sample selection problem associated with the state's decision to adopt and design its RPS policy. Chandler (2009) uses innovation and diffusion theory to see whether a state's RPS policy adoption is dependent on its neighboring states' behavior. The paper finds that states within same census regions and sharing same border have statistically significant impact in the adoption of a state's own RPS policy (Chandler, 2009). Berry and Berry (2007) argue that a state may follow its neighboring states' policy for various reasons. State may learn from its surroundings or it might want to be competitive or it may do so due to the public pressure. Additionally, the social contagion model also supports the argument that RPS status of neighboring states affects state's decision to adopt the policy (Berry & Berry, 2007).

Social contagion model implies that state officials respond according to residents' reaction to a policy change in the neighboring states before deciding to implement similar policy in their state (Pacheco, 2012). With the help of aggregate data on antismoking legislation across US states, Pacheco (2012) finds that neighboring states' policy changes the public opinion and state officials "simply respond to the changing attitudes of their constituents." This paper considers three different geographic boundaries to define neighbors of a state – state that lie in the same census regions, states that belong to same census divisions, and border sharing states[10] (Pacheco, 2012). This gives us three different ways to account the geographic neighbor's impact in the state's RPS choice.

Moreover, I use state-level annual unemployment rate, solar and wind potentials, generation shares from fossil fuels, legislator's environmental score, and gross state per capita as additional variables based on the works of Chandler (2009) and Lyon and Yin (2010). States with high unemployment rate may implement stringent RPS policy with an aim of increasing economic activity (Lyon and Yin, 2010). The environment score is issued by League of Conservative Voters (LCV) "to rate the US Congress members on environmental, public health, and energy issues" (LCV, 2011) and varies between 0 and 100, with 100 being the most environment conscious. The score is based on the important environment legislation – such as issues related with energy, global warming, public health, and spending on environmental programs – and the corresponding voting records of all congressional members of each state (LCV, 2011).

The first-part of the three-part Heckit model (equation 9) is the probit selection equation that determines the state's participation decision in RPS policy. In the first stage, the dependent variable is the RPS status (binary) of a state. We estimate the inverse mills ratios from the probit equation and use it as one of the explanatory variables in the second part of the Heckit model (Wooldridge, 2010). The second-part helps determine the magnitude of RPS policy if a state chooses to adopt the policy. In the second-part, we use Ordinary Least Square (OLS) regression

[10] While considering neighboring states, we do not limit observations to PJM states. The first two stages of Heckit model accounts RPS status of states that lie in the same census region and division.

with the state-fixed where the dependent variable is RPS yearly energy targets. This second stage model (equation 10) gives the linear projection RPS yearly targets. The final stage (equation 11) is the main structural equation in which we use predicted values of the RPS yearly target variable and other exogenous variables of equation 7 to estimate the impact of RPS yearly targets on amount of coal utilized by coal plants. The econometric equations of the three-part model are as follows:

(10) $$RPS = \mu_1 neighbour_{j(t-1)} + \mu_2\, Wind_s + \mu_3 Solar_s + \mu_4\, Unemp_{st} + \mu_5\, M_{st} + \mu_6\, V_{st}$$

(11) $$w_{st} = \alpha_s + \lambda_1\, IMR_{st} + \lambda_2\, Unemp_{st} + \lambda_3\, M_{st} + \lambda_4\, V_{st} + u_{st}$$

(12) $$q_{ist} = \alpha_i + \beta_1 \widehat{w}_{st} + \beta_2 l_{ist} + \beta_3\, m_{st} + \varepsilon_{ist}$$

where, *j* is the geographic level for neighboring states. *RPS* is the binary variable that gives the status of state's RPS policy, $neighbour$ is the percentage of neighboring states implementing RPS policy, *IMR* inverse mills ratio, $Unemp$ is the state's annual unemployment, $Wind$ is the percentage of land area with a gross capacity factor of 30% and greater at 80-m height above the ground in a state (NREL and AWS, 2011), *Solar* is the cumulative estimated annual technical potential capacity for solar power technologies such as utility-scale photovoltaic (PV), rooftop PV, and concentrating solar power, M represents electricity market related variables, and V is a vector of socio-economic variables. Wind and solar potential– state specific time invariant variables – are not included in equation 10 due to the use of state fixed effect.

6. Data

This paper uses fuel receipts and deliveries information, electricity generation, and RPS related data to analyze the quantity of coal used by coal-fired plants. The analysis is includes 260 unique coal plants of PJM region from 2002 to 2011 covering both pre-RPS and post-RPS era. In addition, for addressing the selection issue, the model uses state-level data on renewable potential, electricity price, fuel prices, and socio-economic variables.

6.1 Coal related variables

The source of monthly fuel deliveries is EIA 423[11], FERC 423, and EIA 923[12] survey forms available in Energy Information Agency (EIA) website. The EIA collects data on fuel deliveries of coal-fired utilities with nameplate capacity greater than 50 MW. Prior to 2008, EIA collected fuel information using two separate forms – FERC 423 for regulated power plants and EIA 423 for non-utility plants. These two survey forms were merged into EIA 923 – Schedule 2 since 2008. Some of the variables of interest from the EIA survey forms are coal purchase quantity, coal attributes such as calorific values, ash values, and sulfur content.

6.2 RPS data

The sources of RPS yearly target variable are the Database of State Incentives for Renewable Energy[13] (DSIRE) and Union of Concerned Scientists[14] . In this study, states are first separated in two groups – RPS states and non-RPS states. States that have mandatory RPS yearly targets in effect by 2010 are the RPS states. All other states are non-RPS states. Thus, non-RPS states also

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[11] EIA 423 and FERC 423: http://www.eia.gov/electricity/data/eia423/

[12] EIA 923: http://www.eia.gov/electricity/data/eia923/

[13] DSIRE: http://www.dsireusa.org/rpsdata/index.cfm

[14] UCS: http://go.ucsusa.org/cgi-bin/RES/state_standards_search.pl?template=main

contain states that have voluntary RPS policy[15] or states that have passed RPS policies that only become effective after 2011.[16]

6.3 Electricity and Fuel related variables

The EIA collects data on electricity prices and fuel prices. The electricity price is the annual weighted average of residential, commercial, and industrial prices for any state. Monthly state-level natural gas price are also collected from EIA. The econometric model uses average gas price charged to electric power producers. Similarly, the source of state-level coal price data is annual coal report published by EIA. The paper uses average price of coal delivered to electric power sector for each state to control for the impact of change in the coal price in coal consumption.

6.4 Addressing Selection Problem: State-level data

The source of state-level wind[17] and solar resource potential is National Renewable Energy Laboratory based on available resources, technology, and geographical limitations. The gross state product per capita (GSP per capita) and the national environmental score from League of Conservative Voters (LCV) are used to control for socio-economic factors. The source of annual GSP which is in 2005 dollar terms is taken from the Bureau of Economic Analysis (BEA).[18]

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[15] IN and VA have voluntary RPS mandates (DSIRE, 2011).

[16] MI will make RPS mandatory in 2012 (DSIRE, 2011).

[17] Wind resource potential: http://www.windpoweringamerica.gov/windmaps/resource_potential.asp

[18] GSP data: http://www.bea.gov/regional/

Midyear population data is obtained from the US Census Bureau.[19] The LCV score is the average of the scores give to house and senate members of each state (LCV scorecard, 2012)[20].

7. Descriptive Statistics

The final dataset contains approximately 2200 annual-level observations of 260 unique PJM territory coal plants from 2002 to 2011. Table 1 reports definitions, means, and standard errors of the variables. The mean calculation is further subdivided into four categories – coal plants in non-RPS states, plants in RPS states, plants in RPS states before the policy was enacted, and coal plants in the RPS states after the policy went into effect.

On average, coal plants in PJM states purchased 1.74 million tons of coal each year to generate an average of 4.01 TWh of electricity. Whereas, coal plants for non-RPS states bought 1.92 million tons of coal and the average amount of coal procured by plants from RPS states is 1.59 million tons. Average electricity generation by coal plants in non-RPS states is 20 percent greater than the plants in the RPS states. Similarly, after RPS policy went into effect, coal plants of RPS states purchased average of 1.53 million tons of coal and produced 3.42 TWh of electricity annually. Figure 1 gives the average annual coal purchase of coal plants according to the different categories specified in the table 1.

[19] State population data: http://www.census.gov/popest/data/historical/index.html

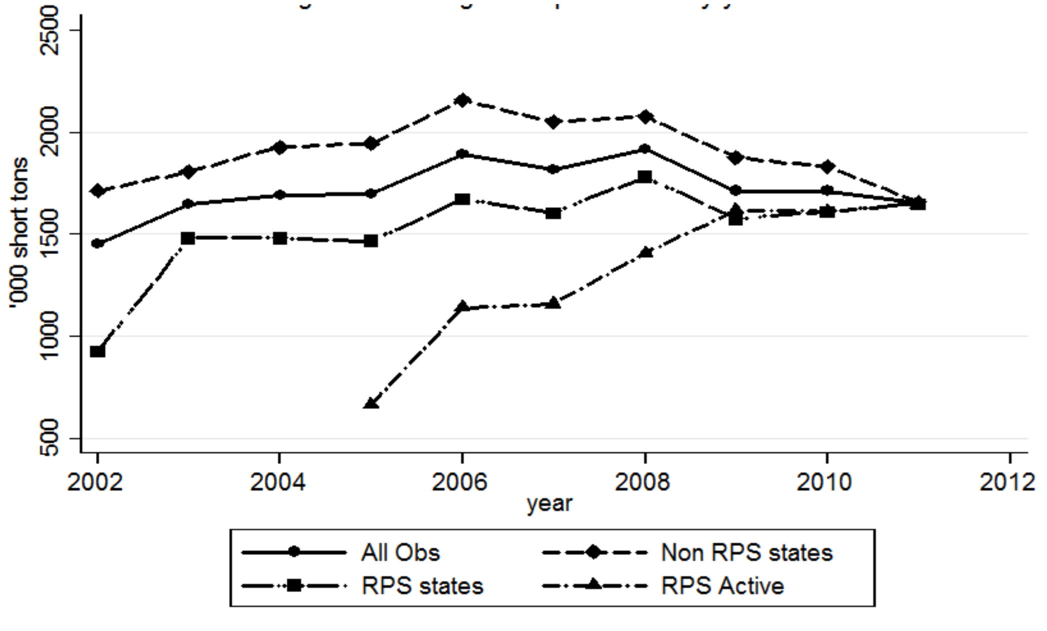
[20] LCV Scorecard: http://www.lcv.org/scorecard/scorecard-archives/

Table 2-1: Variable definitions, Means, and Standard Errors

Variable definition	*All obs*	*Plants in non-RPS States*	*Plants in RPS states*	*Plants in RPS States - before active RPS*	*Plants in RPS states- after active RPS*
coal_quantity	1,745.5	1,917.0	1,592.3	1,641.6	1,526.7
	44.8	72.7	54.2	72.9	81.0
plant_annual_gen	4,015.3	4,502.3	3,584.3	3,704.4	3,423.6
	101.1	155.3	130.8	177.2	192.9
quantity_gwh	2.01	2.72	1.39	1.79	0.85
	0.58	1.10	0.51	0.88	0.16
quantity_sum_cap	2.99	2.73	3.22	3.19	3.27
	0.04	0.04	0.07	0.09	0.13
quantity_name_cap	2.72	2.47	2.95	2.93	2.97
	0.04	0.04	0.07	0.08	0.11
ash_ave	10.97	9.99	11.85	11.06	12.91
	0.18	0.18	0.30	0.34	0.54
sulfur_ave	1.47	1.48	1.46	1.41	1.54
	0.02	0.03	0.03	0.04	0.05
btu_ave	22.63	23.06	22.25	22.37	22.09
	0.15	0.28	0.12	0.15	0.20
fuel_cost_ave	153.94	187.96	112.07	171.90	70.46
	2.99	3.14	5.00	6.19	6.56
total_elec_price	7.91	6.97	8.74	7.74	10.08
	0.04	0.05	0.05	0.03	0.07
coal_price_electric	45.88	43.86	47.77	40.51	57.05
	0.40	0.45	0.64	0.73	0.96
gas_price_elec	6.83	6.48	7.12	7.86	6.15
	0.05	0.07	0.07	0.07	0.10
No of Observations					
No of Unique Plants					
No of States					

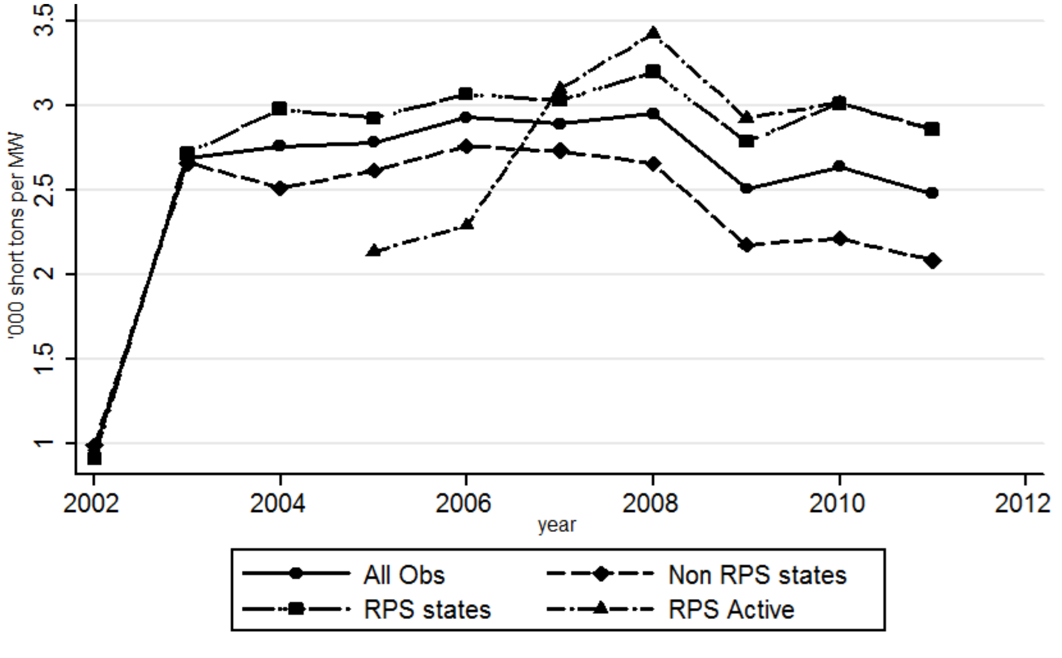
Figure 1 shows that coal plants' average coal purchase increased for all categories from 2002 to 2011. Figure 1 shows that average coal purchase for plants in non-RPS states is higher than that of the RPS states. Second, over time, the average coal purchase increases significantly for coal plants that lie in the RPS enacted states. This may be because states with bigger coal plants adopted RPS in later years; Maryland in 2006, Pennsylvania in 2007, and both Delaware and Illinois in 2008.

Figure 2-1: Average coal purchased by year



The paper uses the ratio of quantity of coal purchase to the nameplate capacity as an alternative dependent variable in order to control for the size of a coal plant. Table 1 shows that on average coal plants purchased 2.72 thousand tons per MW. The coal utilization per MW differs among plants in non-RPS and RPS states – on average, plants in RPS states utilized 20 percent more coal per MW of plants' capacity than the plants that are in the non-RPS states. The plot of average quantity/capacity by year in figure 2 shows the differences among four groups of plants. Here, graph of quantity per capacity for RPS states is always greater that of non-RPS states coal plants. Similarly, table 1 shows that coal specific characteristics such as ash values, sulfur values, and calorific values do not vary significantly among different groups of states. This shows that coal attributes have not changed significantly during the period of the study.

Figure 2-2: Average coal purchased per MW by year



The purpose of this study is to estimate the impact of RPS targets on the amount of coal purchased by the coal plants. Figure 3 is the scatter plot of the amount coal purchased and states' RPS yearly targets. It also contains a fitted line that gives the average coal purchase at different RPS yearly energy targets. The figure shows a direct relationship between the average amount of coal purchased by plants and state's RPS mandates. It demonstrates that the coal plants in states with stringent RPS annual requirements purchase less amount of coal compared with the coal plants in the states with lower RPS targets.

Both state-level fuel prices and electricity price is higher in RPS states than non-RPS states. Figure 4 gives the annual average state-level fuel prices for power plants from 2002 to 2011. The average retail coal price doubled during the period of study, whereas natural gas price has shown the reverse trend – it decreased considerably in the recent years due to the surge in shale gas production.

Figure 2-3: Quality of coal purchased and RPS yearly mandates

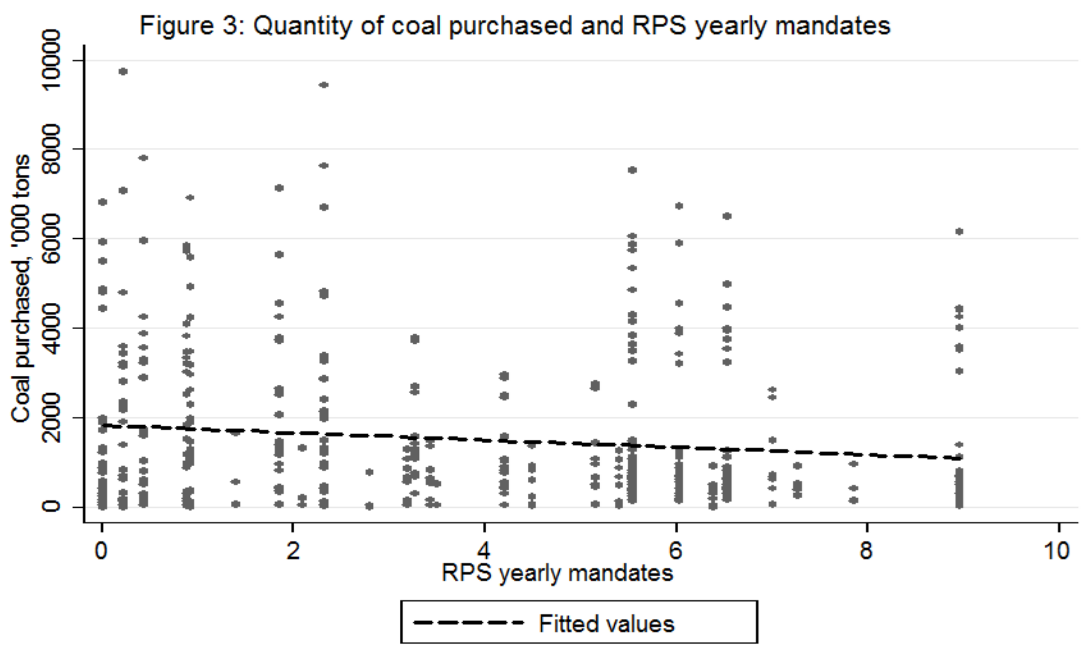
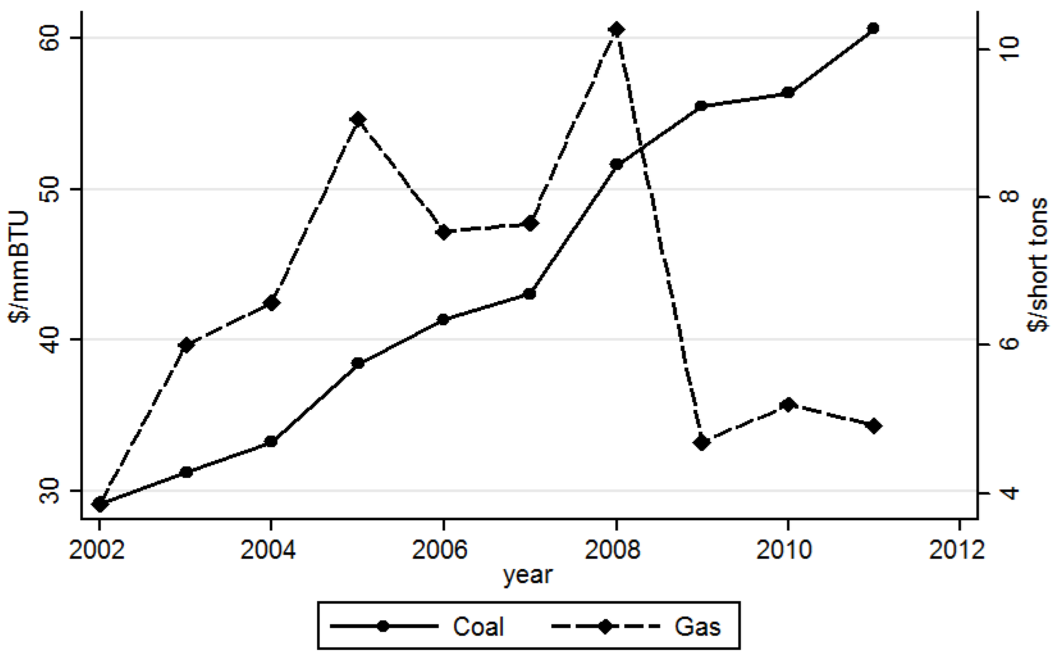


Figure 2-4: Average fuel prices by year



8. **Analysis and Results**

This section presents the regression results to determine the impact of RPS policy on fuel purchase by PJM states' coal plants. Table 2 contains the OLS results when the dependent variable is annual coal purchased by plant. Tables 3 – 5 are the results of three-part Heckit model for addressing the selection issue. For robustness check, an additional dependent variable – the ratio of coal purchase to plant's nameplate capacity – is used. Tables 6 and 7 contain OLS results and selection corrected results, respectively. All the models include plant-fixed effects and year-fixed effects. Standard errors are robust and clustered at the plant-level.

8.1 Ordinary Least Square Estimation

The first column of table 2 only includes yearly RPS targets with plant- and year-fixed effects. The subsequent models account different sets of control variables – coal properties (column 2), fuel prices (column 4), and electricity prices (column 5).

The base model shows that RPS yearly energy target is associated with an increase in the coal purchased by coal-fired plants – a percentage point increase in yearly energy target increases plant's coal purchase by 38.8 thousand tons. The results are consistent and statistical significant after other covariates are added in the model. In the final model, column 4, regression result suggests that one percentage point increase in RPS yearly energy target raises plant's coal purchase by 42.3 thousand tons.

The column 2 of table 2 controls for the coal –specific characteristics. The results fail to show the statistical significance of coal-specific characteristics such as ash values, sulfur and heat contents on the quantity of coal utilized. Even though boilers are designed to use coal within certain range of moisture, plants may purchase coal with wide range of ash values and blend them to get in the boiler's accepted range (Carpenter, 1995). Thus, the tendency of blending may be a reason of not seeing the impact of ash values in the amount of coal purchase. Similarly, the introduction of sulfur emissions cap and trade through Clean Air Act of 1990 also limited sulfur emissions from coal-fired plants.

The regression result from column 3 of table 2 implies that coal price has negative and statistical significant impact in the amount of coal purchase – one-dollar increase in coal price per ton reduces the amount of coal purchase by 9.7 thousand tons. Similarly, average electricity price has negative effect in the amount of coal purchase.

Table 2-2: OLS results - Amount of Coal purchased ('000 tons) as dependent variable

	(1)	(2)	(3)	(4)
RPS yearly targets in percentage	38.798**	36.456*	40.838**	42.317**
	(19.371)	(19.139)	(20.706)	(20.786)
Coal Ash conents, % by weight		-10.529	3.967	2.731
		(32.562)	(32.389)	(32.544)
Coal sulfur conent, % by weight		-105.813	-110.285	-112.849
		(85.221)	(84.965)	(84.591)
Coal Heat content, million btu per physical unit		-32.396	-25.097	-25.022
		(29.175)	(24.664)	(24.883)
Gas price, $/ '000 cu. ft.			-31.252	-11.024
			(50.437)	(50.069)
Coal price, $/short tons			-9.746***	-8.765***
			(3.043)	(2.944)
Electricity price, c/kWh				-112.306***
				(34.506)
Number of observations	*2,060*	*2,059*	*1,666*	*1,666*
Adjusted R2	*0.063*	*0.075*	*0.091*	*0.095*
State fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*

*note: *** p<0.01, ** p<0.05, * p<0.1*

8.2 Addressing Selection Bias

Table 3 contains the result of probit selection model where the dependent variable is the dichotomous variable indicating RPS status of a state. The result of second stage Heckit model where dependent variable is the annual RPS yearly targets is presented in table 4. From the second-stage, we calculate the linear prediction of RPS yearly targets by restricting observations to non-zero RPS yearly target variable. Table 5 contains empirical results of the final stage of the three-part model, the base model of the study, which uses the selection-corrected estimates of RPS target levels to find the impact of RPS on coal utilization.

Each column in table 3 shows regression results by accounting geographic neighbors in three different ways. Probit results show that the RPS status of states in the same census region and division has positive and statistically significant effect on a state's own RPS adoption. This result is similar to Chandler's (2009) findings and suggests that geographic proximity with RPS states influences a state's decision to implement the policy. Similarly, variables like solar potential, LCV score, and GDP per Capita have positive and statistically significant impact when a state is making a decision of RPS adoption. Results show that state's solar potential has significantly positive impact while making RPS decision. The probit results fail to show the significance of state's windy land in adopting RPS policy.

Table 4 presents the results of the second-stage Heckit model where the dependent variable is RPS yearly energy targets. The coefficients of inverse mills ratio are significant in two neighboring groups suggesting that there is a selection issue related with state's decision to adopt the RPS policy. Similarly, the results show that annual coal and gas prices have negative impact in state's RPS yearly energy targets. State's average environmental score has positive and significant effect in introducing stringent RPS mandates. Similarly, the results show that richer states have higher RPS yearly targets. Table 5 presents the regression results of the selection corrected base model.

The first column of table 5 is the OLS results presented in the fourth column of table 2. The second column of table 5 presents results where states that lie in the same US census region are considered as neighbors. Similarly, in column 3, states that lie in the same US census divisions are neighbors. The final column of table 5 considers states that share geographic border to be neighbors.

The OLS regression results suggest that one percentage point increase in RPS yearly target level raises coal purchase amount by 42.3 thousand tons. The results after addressing selection of RPS policy are similar to the OLS results. When states in same census regions are grouped together to be neighbors, the results show that one percentage point increase in RPS levels is associated with additional 74.8 thousand tons of coal utilization for the coal plant. The impact of RPS increases when states in the same census divisions are considered to be neighbors. However, when border sharing states are taken as neighbors, the results suggest that one percentage point in RPS mandate increases annual coal purchases by 50.5 thousand tons. In all the selection corrected models, we find the impact of RPS to be higher than the OLS results. The results are different than what we hypothesized.

The analysis showing the positive impact of RPS yearly targets on PJM coal plants' coal purchases is opposite to what we hypothesized and may suggest few things. Due to the nature of coal plants and low coal prices during the period of the study, there may be fewer coal-fired utilities operating at the margin, thus RPS do not impact the coal plants the way we hypothesized. Moreover, RPS yearly energy targets are fairly low at present; they are scheduled to increase considerably in coming years. RPS may decrease the amount of fuel utilized by coal-fired utilities when RPS mandates increase in future.

The operational strategy of the coal plants may also explain the increase in the amount of coal purchase. Grid operator or coal plants may pay wind farms to curtail their generation (Rogers et al, 2010). Similarly, biomass co-firing may be another reason why RPS doesn't impact the way we hypothesized. RPS may have encouraged co-firing tendency among coal plants, which in turn will increase the amount of coal used for generation. Plants blend coal with biomass, and biomass can be used to meet the RPS requirement. Biomass co-firing allows coal plants to reduce greenhouse gas emissions and also count towards RPS mandates or various pollution-reduction incentives (Basu et al., 2011). Stringent carbon policies make co-firing more attractive, since the process is carbon neutral, living biomass absorbs CO_2 and then it is released during the co-firing, and can qualify towards credits. Biomass co-firing trend is increasing in US due to the low modification cost of existing coal plants, increase fuel flexibility, and cheaper cost of biomass than coal. There are more than 40 co-firing coal plants in US (IEA Bioenergy Task force 32).

Table 2-3: Probit regression for RPS selection - RPS status as dependent variable

	Census region	*Census division*	*Border sharing*
Percentage of RPS states in census region	0.130**		
	(0.052)		
Percentage of RPS states in census division		0.072**	
		(0.031)	
Percentage of RPS states that share border			0.013
			(0.009)
Wind potential state (%)	0.106	0.090	0.071
	(0.066)	(0.060)	(0.047)
Solar Tehnical Potential (TW)	-1.410*	-1.291*	-1.103***
	(0.755)	(0.693)	(0.420)
Annual unemployment rate (%)	0.214	0.115	0.332**
	(0.232)	(0.221)	(0.151)
Petroleum share generation (%)	-0.196	-0.190	-0.161
	(0.251)	(0.200)	(0.132)
Natural gas share generation (%)	-0.122**	-0.115**	-0.099***
	(0.059)	(0.054)	(0.029)
Coal share generation (%)	-0.016	-0.018	-0.016***
	(0.011)	(0.011)	(0.006)
LCV score	0.071**	0.056**	0.031**
	(0.029)	(0.025)	(0.015)
GDP capita	236.1**	225.8**	187.0**
	(110.7)	(97.2)	(53.4)
Number of observations	*130*	*130*	*130*
Adjusted R2	*0.774*	*0.764*	*0.659*

*note: *** p<0.01, ** p<0.05, * p<0.1*

Table 2-4: Second stage results - linear prediction of RPS yearly targets

	Census region	*Census division*	*Border sharing*
Inverse mills ratio - census region as neighbors	0.725***		
	(0.150)		
Inverse mills ratio - census division as neighbors		0.464	
		(0.286)	
Inverse mills ratio - border sharing states as neighbors			1.958***
			(0.297)
Annual unemployment rate (%)	-0.230	-0.267	0.239
	(0.309)	(0.378)	(0.327)
Petroleum share generation (%)	-0.158**	-0.116	-0.366***
	(0.063)	(0.084)	(0.084)
Natural gas share generation (%)	-0.068**	-0.053	-0.145***
	(0.026)	(0.038)	(0.033)
Coal share generation (%)	-0.012	-0.018	-0.029***
	(0.009)	(0.012)	(0.009)
Electricity price, c/kWh	0.377	0.498	0.343
	(0.289)	(0.325)	(0.278)
LCV score	0.059***	0.037*	0.060***
	(0.019)	(0.022)	(0.021)
GDP capita	200.2***	177.7***	284.5***
	(62.0)	(77.3)	(69.2)
Number of observations	*130*	*130*	*130*
State fixed effects	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*

*note: *** p<0.01, ** p<0.05, * p<0.1*

Table 2-5: OLS and Selection Corrected Results - Coal purchased ('000 tons) as dependent variable

	OLS	*Census region*	*Census divisions*	*Border sharing states*
RPS yearly targets in percentage *(linear prediction from second stage of Heckit model)*	42.3**	74.8**	118.8**	50.5**
	(20.786)	(35.234)	(48.044)	(33.953)
Coal Ash conents, % by weight	2.731	4.967	5.529	4.534
	(32.544)	(32.998)	(32.342)	(32.964)
Coal sulfur conent, % by weight	-112.849	-99.918	-98.111	-104.990
	(84.591)	(84.234)	(84.206)	(84.627)
Coal Heat content, million btu per physical unit	-25.022	-26.174	-25.486	-25.728
	(24.883)	(24.556)	(24.476)	(24.650)
Gas price, $/ '000 cu. ft.	-11.024	-15.513	2.610	-23.936
	(50.069)	(49.025)	(49.427)	(49.404)
Coal price, $/short tons	-8.765***	-9.357***	-11.701***	-9.852***
	(2.944)	(3.061)	(3.336)	(3.133)
Electricity price, c/kWh	-112.3***	-141.0***	-160.4***	-121.9***
	(34.5)	(37.5)	(40.2)	(35.7)
Number of observations	*1,666*	*1,666*	*1,666*	*1,666*
Adjusted R2	*0.095*	*0.091*	*0.094*	*0.089*
State fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*

*note: *** p<0.01, ** p<0.05, * p<0.1*

8.3 Robustness Check – coal purchase/capacity as dependent variable

The empirical analysis uses the ratio of coal purchase to the nameplate capacity of the coal plant as another dependent variable for robustness check. Dividing coal purchase amount with the capacity of the plant helps to control for the size of the plant and also allows looking at the extent at which the plant is utilized. Table 6 presents OLS results where the dependent variable is the ratio of annual coal purchases to the nameplate capacity of the coal plant. The independent covariates are same as used in earlier models. Column 1 of table 6 estimates one percentage point increase in RPS level increases the coal usage by 58 tons per MW. The results are consistent after controlling for coal-specific characteristics and fuel prices. Coal specific attributes such as ash values and calorific are negatively related with the ratio of coal purchase to plant's capacity. Table 7 contains selection-corrected results for quantity/capacity variable. The regression results show that current *(low)* RPS target levels do not have statistical significant impact in coal plants fuel utilization.

Our regression results show that RPS increase the amount of coal purchase by coal plants, whereas we fail to show the impact of the policy on the ratio of coal purchase to the plant's size. It may be the case that during the period of the study, efficient and low-cost coal plants remain in operation whereas inefficient plants are shut down. And the remaining coal plants operate at the full capacity. As a result, the amount of coal purchase by operating coal plants increases.

Table 2-6: OLS results - Amount of coal purchased per name plate capacity ('000 ton/MW) as dependent variable

	(1)	(2)	(3)	(4)
RPS yearly targets in percentage	0.058*	0.055*	0.062*	0.065*
	(0.033)	(0.033)	(0.036)	(0.036)
Coal Ash conents, % by weight		-0.061**	-0.059*	-0.062*
		(0.030)	(0.035)	(0.035)
Coal sulfur conent, % by weight		0.005	0.017	0.012
		(0.071)	(0.081)	(0.080)
Coal Heat content, million btu per physical unit		-0.029*	-0.025*	-0.024*
		(0.016)	(0.015)	(0.015)
Gas price, $/ '000 cu. ft.			-0.063	-0.024
			(0.048)	(0.049)
Coal price, $/short tons			-0.011	-0.009
			(0.009)	(0.009)
Electricity price, c/kWh				-0.215***
				(0.053)
Number of observations	1,998	1,997	1,622	1,622
Adjusted R2	0.075	0.083	0.090	0.097
State fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*

note: *** p<0.01, ** p<0.05, * p<0.1

Table 2-7: OLS and Selection Corrected results - Amount of coal purchased per nameplate capacity ('000 ton/MW) as dependent variable

	OLS	*Census region*	*Census divisions*	*Border sharing states*
RPS yearly targets in percentage *(linear prediction from second stage of Heckit model)*	0.065*	0.013	0.047	0.003
	(0.036)	(0.051)	(0.063)	(0.057)
Coal Ash conents, % by weight	-0.062*	-0.063*	-0.062*	-0.063*
	(0.035)	(0.035)	(0.035)	(0.035)
Coal sulfur conent, % by weight	0.012	0.015	0.019	0.014
	(0.080)	(0.085)	(0.083)	(0.085)
Coal Heat content, million btu per physical unit	-0.024*	-0.026*	-0.026*	-0.026*
	(0.015)	(0.014)	(0.014)	(0.014)
Gas price, $/ '000 cu. ft.	-0.024	-0.073	-0.059	-0.077
	(0.049)	(0.051)	(0.049)	(0.050)
Coal price, $/short tons	-0.009	-0.010	-0.010	-0.010
	(0.009)	(0.009)	(0.009)	(0.009)
Electricity price, c/kWh	-0.215***	-0.209***	-0.224***	-0.203***
	(0.053)	(0.047)	(0.054)	(0.047)
Number of observations	*1,622*	*1,622*	*1,622*	*1,622*
Adjusted R2	*0.097*	*0.087*	*0.087*	*0.087*
State fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*

*note: *** p<0.01, ** p<0.05, * p<0.1*

9. Conclusion

In this paper, I study the change in PJM coal plants' fuel utilization due to renewable portfolio standards. I develop a panel dataset comprising plant-level data of annual coal purchases, coal characteristics, and electricity and fuel price variables. The results from the OLS regression of base model suggest that mandatory RPS yearly energy targets, which are adjusted for load covered by each state's RPS policy, are statistically significant in increasing annual coal purchases. Moreover, I address the selection problem of states' decision to adopt and design RPS policy with the help of the Heckit model.

The first-stage of the Heckit model is the probit selection equation where the dependent variable is dichotomous indicating the RPS status of a state. From the second-stage, we estimate the linear prediction of RPS yearly targets by restricting observations to non-zero RPS yearly targets variable. In the first and second stages, dependent variables are each regressed over factors that affect state's decision to adopt and design RPS policy and exogenous variables of the base model. Variables that impact RPS adoption and design process are the RPS statuses of its neighboring states, state's annual unemployment rate, and state's solar and wind potential.

The base model shows that RPS yearly energy targets increase the amount of coal purchased by coal-fired plants. The OLS results with plant fixed effects show that one percentage-point increase in state's yearly energy target increases the average plant's coal purchase by 42,000 tons. These results are approximately consistent across selection-corrected models. The analysis showing the positive impact of RPS yearly targets on PJM coal plants' coal purchases is opposite to what we hypothesized and may suggest that fewer coal plants are operating in the margin. Moreover, curtailment payments and increase in biomass co-firing may also explain the counter intuitive impact of RPS on coal-fired generation.

There is couple of avenues for future research work. States with different market structures have implemented RPS policy with an aim of increasing renewable generation and reducing greenhouse emissions. The obligations to meet RPS vary according to the market structure of state's electricity sector. For example, in PJM where most of the states have deregulated electricity market, distribution utilities are mandated to meet the target. Whereas, fossil fired plants have obligation to comply with the RPS policy in states with the regulated market such as Midwest Independent Transmission System Operator, Inc. One of the future works is to look at the impact of RPS in coal plants in the regulated electricity market. The obligation to meet the

RPS target according to the electricity market structure also brings up the issue of social welfare. Thus, the other research area is to compare the efficiency of RPS policy among regulated and competitive electricity market.

10. **References**

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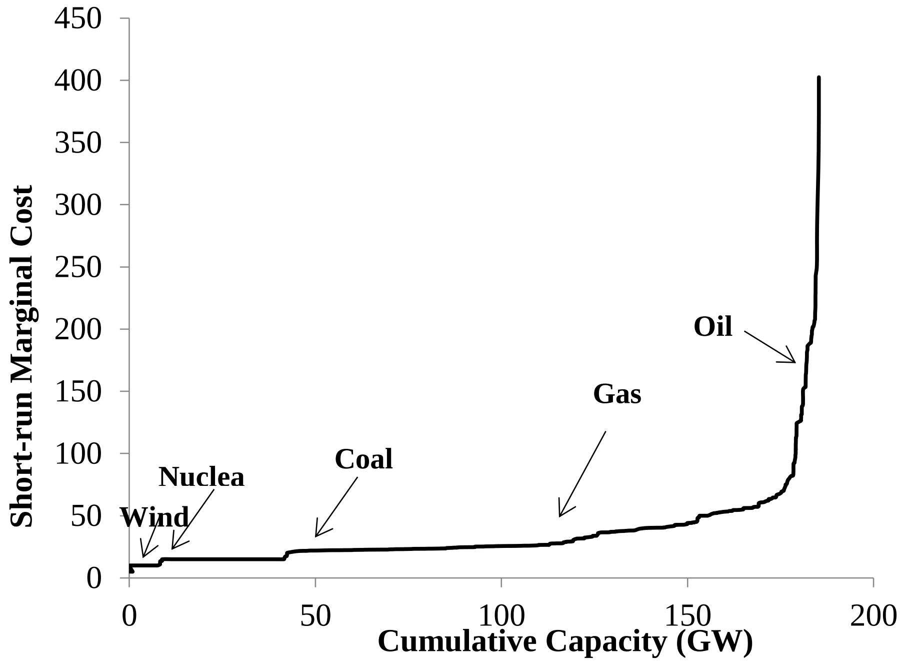
11. **Appendix**

Figure 2-5: Short-run electricity supply curve



Chapter 3: Residential Customers Response to Critical Peak Events of Electricity: Green Mountain Power Experience

Abstract:

Demand response (DR) programs, usually through peak pricing and incentive-based approaches, can encourage customers to reduce or shift consumption during peak periods. This benefits utilities by lowering short-run generation costs and reducing the need for some long-run peak-driven investments. This paper analyzes the impact of Vermont's Green Mountain Power's (GMP) emergency DR programs on residential customers' electricity consumption during a two-year pilot study program in 2012–2013. We examined potential peak load reductions, monthly electricity consumption, and persistence of responses with the help of difference-in-difference approaches. We created a panel dataset combining hourly electricity load, critical peak event information, weather variables, and participant specific characteristics. The 3,735 single-home residents of Central Vermont area were separated into six treatment groups and two control groups resulting into 26 million hourly load observations during the period of the study.

Our analysis shows that incentive-based demand response programs have statistically significant impacts on reducing peak load. Specifically, CPR rates reduced peak load usage 6% to 7.7% and CPP rates reduced peak load between 6.8% and 10.3% during critical peak events. Moreover, on average, IHD-equipped participants' monthly energy consumption was 2.0% to 5.3% lower than the monthly energy usage of non-IHD customers. However, none of the CP rate and IHD treatments induced a persistent response across multiple critical events and none of the treatment groups exhibited a consistent response to critical peak events. Based on our evaluation of GMP's DR programs during 2012 and 2013, neither critical peak pricing nor rebates are themselves sufficient to substitute for new capacity to meet resource adequacy requirements.

Keywords: demand response, smart grid, critical peak events, electricity, load shifting, consumer behavior

1. **Introduction**

The limited and costly electricity storage system makes meeting dynamic electricity demand, especially during peak period, challenging and economically inefficient. A Large amount of generating capacity has to be kept in the reserves to supply electricity during high demand periods. At the same time, transmission and distribution systems need to be able to accommodate peak electricity demands resulting in high reliability cost. Demand response (DR) programs, usually through peak pricing and incentive-based approaches, can reduce peak electricity demand by encouraging customers shift their consumption. A Federal Electric Regulatory Commission report estimates that DR programs were responsible potential peak load reductions of 66,351 MW in 2012, a 25% increase from 2010. Besides increasing electric grid reliability, DR programs also benefit utility companies by minimizing new infrastructure and thus saving huge capital costs. This paper analyzes the impact of emergency DR programs on the electricity consumption behaviors of residential customers of Rutland, VT during a two-year pilot study in 2012-2013.

Relevant literatures have examined the impact of different types of demand response programs in residential customers' electricity usage. Cappers et al. (2010), Faruqui et al. (2010), and Lave, Lester, and Spees (2007) provide overviews on the scope demand response programs. Herter et al. (2007) use California Statewide Pricing Pilot of 2003-04 dataset to analyze residential customers' electricity consumption due to critical peak pricing. Another paper by Herter and Wayland (2007) find the average reduction in load during critical peak events was 5.1 %. A working paper by Houde et al. look at the impact of smart meters in the daily electricity consumption where the continuous feedback system help to reduce consumption by 5.7 %.

Green Mountain Power (GMP) launched critical peak events during summers of 2012 and 2013 with the help of two time-based emergency DR programs – critical peak pricing (CPP) and critical peak rebate (CPR) – coupled with the in-home display (IHD) equipment. Critical peak pricing treatment charges a very high pre-determined electricity price during the critical event period, whereas CPR provides incentives to participants for reducing consumption below their baseline. In-home display technology allows a two-way communication between customers and electricity grid showing information on real-time electricity consumption and critical peak events. The two-year pilot study focuses on single-home residents of Rutland area that face predetermined high electricity retail prices during the critical peak events or receive incentives for reducing consumption from their baseline depending on the participants' treatment rate type. The 3735 single-home residents of Rutland area are separated into six treatment groups and two control groups resulting into 26 million hourly load observations during the period of the study.

The paper's primary interest is to predict the impact of different treatment rates and information system in real-time electricity usage. We create a panel dataset combining hourly electricity load, critical peak event information, weather variables, and participant specific characteristics. We use difference-in-difference regression approach starting with randomized control treatment (RCT) analysis followed by randomized encouragement design (RED). The paper also conducts persistence analysis to analyze customers' responses within different time periods of the critical peak event, specifically within critical peak event hours, event-to-event analysis, and inter-year analysis. Furthermore, the paper also estimates the impact of real time electricity feedback system on energy consumption. Customers equipped with the IHD technology can look at their real time electricity usage and can adjust their consumption pattern.

Our study provides a detailed analysis spanning over two years combining with customer-specific characteristics information. Most of the emergency demand response pilot studies are conducted in hotter regions in terms of climate; this study provides an insight to consumers' electricity usage patterns that face relatively mild summer. The participants of the study mostly live in single-home residents, thus the study is carefully designed to control for heterogeneity in electricity consumption that may arise due to participants living in different residence types and climate zones.

Our analysis shows that incentive-based demand response programs have statistically significant impacts on reducing peak load. Specifically, CPR rates reduced peak load usage 6% to 7.7% and CPP rates reduced peak load between 6.8% and 10.3% during critical peak events. Moreover, on average, IHD-equipped participants' monthly energy consumption was 2.0% to 5.3% lower than the monthly energy usage of non-IHD customers. We also examined participants' electricity usage patterns across different critical peak event periods. We observed that customer responses were quite persistent during the hours of the critical peak event, suggesting that customers take response actions at the beginning of critical peak times or prior to the start of the critical peak period, rather than managing their electricity usage on an hour-to-hour basis during critical peak events.

However, none of the critical peak event rate and IHD treatments induced a persistent response across multiple events and none of the treatment groups exhibited a consistent response to critical peak events. Therefore, the use of rate structures and information feedback alone provide insufficient motivation for consumers to reduce demand in any consistent way across multiple event periods. Based on our evaluation of GMP's DR programs during 2012 and 2013, neither critical peak pricing nor rebates are themselves sufficient to substitute for new capacity to meet resource adequacy requirements.

The rest of the paper follows with a brief description of demand response programs and their statuses in United States in section 2. A review of relevant literature is discussed in section 3. In section 4, the paper sheds light on GMP's pilot study program, its participant selection process, and other related information. The theory underlying emergency demand response programs and econometric methods for analysis are discussed in section 5. Section 6 contains descriptive statistics followed by the discussion of results in section 7. Section 8 concludes the paper.

2. **Demand Response**

Demand Response varies considerably among electric entities and geographic regions, mainly in customer types and participation, programs, and ownership (FERC, 2012). Most of the US DR programs can be grouped into two categories – incentive-based and time-based programs. Incentive-based programs comprise of market-based approaches such as demand bidding, emergency DR, capacity market, ancillary service markets, direct control, spinning and non-spinning reserves, and interruptible/curtailment programs (Albadi and El-Saadany, 2008; FERC, 2012). Similarly, time-based programs consist of critical peak price, critical peak rebate, time of use, and real-time pricing (FERC, 2012).

Albadi and El-Saadany (2008) categorize the benefits of DR in four groups – participant, market-wide, reliability, and market performance. DR participants get financial benefits through energy savings and incentive payments. Demand response programs provide market-wide benefits by reducing electricity price and market power of peaking plants. During high demand period, high marginal cost peaking plants have to be brought online to fulfill the demand.

Infrastructures that serve peak demand remain idle for most of the time and thus will be underutilized. It is economical to shift some of the peak demand to off-peak period and demand response allows changing the electricity consumption pattern. At the same time, DR may lower the wholesale electricity price since the reduction on potential peak load decreases the use of high marginal cost peaking plants. Moreover, lower dependence in peaking plants and potential decrease in wholesale electricity price also reduces the market power of peaking plants.

Demand response programs increase the reliability of the electric system. Frequent changes in demand pattern can affect the grid and may lead to rolling blackouts. Demand response can offset frequent large changes in the amount of electricity demanded and the need of large reserve generation. Even though the main reasons of California's electricity debacle of May 2000 to June 2001 are disputed, there is a general consensus that lack of real time retail electricity pricing is one of the causes.

However, implementation of DR programs comes incurs both capital and operating costs. Both utility company and end-user customers need new technologies for real-time metering and two-way communication. For the utility company there are additional costs for marketing, educating customers, incentive payment, billing, and lost revenue. Similarly, participants also have costs associated with smart meters, energy efficient electric appliances, and inconvenience.

2.1 Status of Demand Response programs in United States

United States has made significant progress in increasing the scope of both residential and commercial DR programs in recent years. The Energy Policy Act of 2005 directed Federal Electric Regulatory Commission (FERC) to prepare annual report on DR and advanced metering[21]. The 2012 report comprised of 1900 respondents of FERC-731 survey form finds that the DR programs were responsible for 66,351 MW of potential peak load reductions (FERC, 2012), a 25 percent increase from 2010. The four most effective DR types, in terms of peak load reduction, are load as a capacity resource, interruptible load, direct load control, and time-of-use (FERC, 2012). However, the report also acknowledges various challenges of DR programs namely lack of time-based DR events for residential customers, estimation and cost-effectiveness of load reductions, and lack of uniform communication and customers' response.

Residential DR programs are not as successful as commercial and industrial programs mainly due to high implementation cost, lack of marketing and education, and lackluster participation. Residential DR programs were responsible for 8,134 MW of peak load reduction, accounting for thirteen percent of total potential peak load of 2012 (FERC, 2012)[22]. However, potential peak load reduction of residential DR programs increased by 13 percent from 2010 to 2012.

The scope and reach of residential DR programs varies considerably according to the electric entities. ISO New England (ISO-NE) provides both day-ahead and real-time DR programs to customers that have communication meters installed and can produce at least 100 kW of load reduction (ISO-NE, 2013a)[23]. The New England ISO serves all or some parts of six North Eastern states – Connecticut, Rhode Island, Massachusetts, New Hampshire, Vermont, and Maine with total generating capacity of 32,000 MW. The all-time peak demand of 28,130 MW

[21] http://www.ferc.gov/industries/electric/indus-act/demand-response/2012/survey.asp

[22] In 2012, commercial and industrial, and wholesale DR programs reduced ~27000 MW and 28,807 MW respectively, whereas residential DR programs were responsible for the total peak load reduction of 8,134 MW during the same period (FERC, 2012).

[23] http://www.iso-ne.com/regulatory/tariff/sect_3/mr1_append-e.pdf Accessed September 2013

was set in August 2006. The ISO expects 400 MW of annual increase in summer peak demand and plans to invest $5 billion in expanding transmission sector for the next 10 years (ISO-NE, 2013b[24].

Pennsylvania-New Jersey-Maryland (PJM) offers incentive-based emergency and economic DR programs in its energy, day-ahead scheduling reserve, capacity, synchronized reserve, and regulation markets (PJM, 2013a).[25] Emergency DR is mandatory with financial penalty for non-compliance and is further divided into three categories – limited, extended for summer, and annual. Whereas economic DR is voluntary based and employed when the prices are "higher than the published monthly PJM net benefit prices" (PJM, 2013b).[26] Furthermore, economic DR programs let end-users provide services in PJM's three different ancillary markets – synchronized reserves, day ahead scheduling reserves, and regulation.

Most notable New York ISO DR programs are day-ahead DR program, Special Case Resources, and Emergency Demand Response Program (EDRP)[27]. The voluntary EDRP has a minimum load reduction requirement of 100 kW per load zone (NYISO, 2013)[28]. The program is based on the measurement and verification of reduced energy consumption coupled with the compensation mechanism.

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[24] http://www.iso-ne.com/nwsiss/grid_mkts/key_facts/ accessed September 2013

[25] Demand Response, PJM: http://www.pjm.com/markets-and-operations/demand-response.aspx accessed September 2013

[26] Customer fact sheet, PJM: http://www.pjm.com/~/media/markets-ops/dsr/end-use-customer-fact-sheet.ashx Accessed September 2013

[27] Emergency Demand Response Program, NYISO: http://www.nyiso.com/public/webdocs/markets_operations/market_data/demand_response/Demand_Response/Emergency_Demand_Response_Program/edrp_mnl.pdf

[28] Minimum reduction for aggregators is 500 kW.

California's DR programs are mostly geared towards large commercial and industrial customers and are administered by regulated investor-owned utilities (CPUC, 2013).[29] California plans to include residential and small customers in the DR programs once they are equipped with smart meters. Similarly, Electric Reliability Council of Texas (ERCOT) offers voluntary based residential load response program[30] that allows customers to reduce electricity consumption independently (ERCOT, 2013). Our study focuses on the impact of emergency DR programs in the residential customers of Rutland, VT. The state of Vermont only has DR programs administered by ISO-NE in state's territory (EERE, 2013).[31] In 2008, Vermont partnered with EnerNOC Inc., to manage and operate DR capacity between government buildings and ISO-NE as a part of ISO-NE's Forward Capacity Market (ENERNOC, 2008).[32] FERC estimates that Vermont's DR programs were responsible for total peak load reduction of 127 MW in 2012, most of which came from emergency DR and interruptible load programs (FERC, 2012).

3. Literature Review

There has been considerable amount of research that look at the impact of demand response and energy efficiency programs in peak load change and energy savings. With the start of electricity restructuring and advancement in technology, various electric entities have explored the option of implementing DR programs in their territory. Cappers et al. (2010)

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[29] *Demand Response*. California Public Utility Commission: http://www.cpuc.ca.gov/PUC/energy/Demand+Response/ Accessed September 2013

[30] Voluntary Load Response, ERCOT: http://www.ercot.com/services/programs/load/vlrp/index Accessed September 2013

[31] Federal Energy Management Program, Energy.gov: http://www1.eere.energy.gov/femp/financing/eip_vt.html Accessed September 2013

[32] State of Vermont Partners with EnerNOC for Demand Response, http://investor.enernoc.com/releasedetail.cfm?ReleaseID=338112 Accessed September 2013.

summarize and provide empirical evidences of demand response programs in the US electricity market. The paper finds that DR resources have potential of reducing summer peak load by 3 to 9 percent, with exception of the Midwest Reliability Organization (MRO) region where the peak load reduction was at 21 percent. Further, they point out that the consumer's reactions to economic DR programs have been inconsistent mainly due to their lack of experiences with the program.

Faruqui et al. (2010) provide three different approaches – retail dynamic pricing, price responsive demand bid, and supply resource bid – to introduce economic demand response programs in MISO's wholesale electricity market. The paper finds that time-based pricing is the most efficient economic DR in MISO. However, the paper also writes that time-based DR programs face hindrance for two reasons - reluctance of regulators to launch dynamic pricing and lack of interval metering. Lave and Spees (2007) imply that customers respond to higher electricity prices and recommend implementing time-of-use and real time pricing. They recommend installing automated system at the end-user side to communicate according to the dynamic pricing and educating customers about the implication of energy cost during the purchase of new appliances.

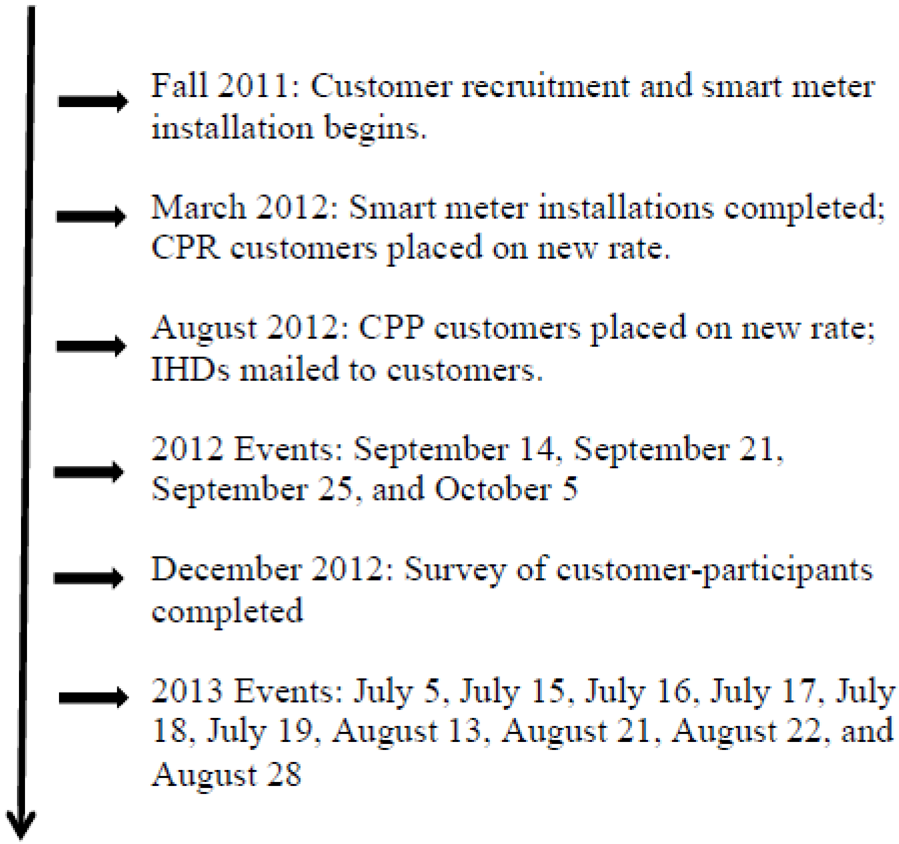
Herter et al. (2007) utilizing a subset of data from the California Statewide Pricing Pilot of 2003-04 look at the impact of critical peak pricing on residential customers' behavior in hourly electric consumption. The study controlled for residence type, temperature, and climate zone. Using graphical analysis, the paper concludes that high price signals have an impact in reduction of hourly load. Moreover, the paper concludes that the reduction is higher if customers are equipped with programmable thermostat rather than manual one. Similarly, Herter and Wayland (2010) find that residential customers, on average, reduce 5.1% of the load due to high electricity prices during the scheduled critical events. They find that the customers' responses are heterogeneous varying across building types and climate conditions.

A working paper of Houde et al. (2011) analyzes the impact of real-time information feedback system in residential electricity consumption. Using yearlong electricity consumption data and difference-in-difference econometric model, they find that the feedback system reduces electricity consumption by 5.7 %. The paper further analyzes participants' time specific electricity usage behavior and persistence in load reduction across the period of the study. The results show that the largest load reduction occurs during morning and evening peak periods. Moreover, the paper also finds that the significant reduction persists up to 4 weeks of the installation of feedback system.

4. **GMP Pilot Study**

Green Mountain Power is conducting a two-year consumer behavior pilot project in Rutland, VT area to study the effect of informational and emergency DR programs on residential electricity consumption. Specifically, the pilot study aims to quantify and compare the impact of time-based DR programs – Critical Peak Pricing (CPP) and Critical Peak Rebate (CPR) – in combination with In-Home Display (IHD) technology on consumers' peak load reduction. Furthermore, the pilot study also looks at the change in energy consumption due to the installation of IHD systems. The study also aims to find the best combination of technical and financial incentives to launch a full-scale DR program to residential customers in near future. Figure 1 displays the timeline of the pilot study during the first year.

Figure 3-1: Timeline of the Green Mountain Power's Study



The GMP Consumer Behavior Study employs randomized control method featuring six treatment groups and two control groups. The combination of two pricing structures with the information and communication system results in six different treatment groups that are as follows:

- **Critical Peak Pricing (CPP)**: A standard flat-rate tariff of \$0.60/kWh during declared critical peak events. For revenue neutrality, customers on the CPP rate pay \$0.144/kWh during non-event hours which slightly lower than the flat-rate customers.
- **CPP with IHD**: Customers in this group receive standard flat-rate as CPP customers, but are provided with the IHD device that gives near-real-time feedback on household energy usage and also receives critical peak time notifications from GMP.
- **Critical Peak Rebate (CPR)**: An incentive based approach where customers receive a rebate of \$0.60/kWh for reducing energy consumption from their baseline during the declared critical peak events. Reduction of energy usage during the peak event is voluntary.
- **CPR with IHD**: Similar rate structure as of CPR group but with the IHD device.

- **CPR to CPP**: Customers are placed in CPR rate structure in year 1 and are moved to CPP treatment in the second year. However, the customers are unaware of the second year rate during the time of enrollment or during the first year of the study.
- **CPR to CPP with IHD**: Similar rate structure with CPR to CPP group, but customers are given IHD device to track electricity usage in real-time and receive critical peak event notifications.
- **Rate 1 with Notification**: Default flat rate of $0.148/kWh in the GMP territory for the residential customers with the notification of critical peak events.
- **Control Groups**: Regular rate with no-notification of critical peak events.

4.1 Participant Selection: Randomization, Eligibility, and Recruitment

The GMP DR study consists of 3735 residential customers selected from randomized sampling of 12,867 customers of Rutland, VT area. Out of 3735 total participants, 1980 are placed in the control group and 1755 participants belong to one of the six treatment groups. The number of customers required for randomization depends on the minimum size of impact of DR on monthly energy consumption and hourly demand load and also on the oversampling rate. The consumer behavior study required a minimum detectable size of 5 percent of average customer-level monthly kWh consumption and 10 percent of average hourly kW demand during the critical event hours. Moreover, the oversampling rate for survey and various treatment groups were determined based on the conservative assumption provided by GMP personnel.

Green Mountain Power took two-step approach to select the eligible customers for randomization. In the first screening phase, GMP made sure that the potential DR participants belonged to Rutland area, lived in single home during the period of the study, had consistent monthly electricity consumption within the range of 50 kWh – 10,000 kWh, and would receive smart meters by summer 2012. In the second stage GMP, with the help of Metrix Matrix, contacted selected customers via phone and mailing and directed customers to a website where they could fill out the eligibility survey. After the completion of the survey, GMP randomly assigned treatment groups and revealed them to customers that it deemed eligible. Metrix Matrix reported that 367 customers declined to participate in the DR study after the treatment rate was revealed to them.

Table 3-1: Required Sample sizes for the Study

Group	Year 1	Year 2	IHD	Notification	Sample size
1	PTR	PTR		X	390
2	PTR	PTR	X	X	195
3	CPP	CPP		X	390
4	CPP	CPP	X	X	195
5	PTR	CPP		X	390
6	PTR	CPP	X	X	195
C1	Flat	Flat			1200
C2	Flat	Flat			390
C3	Flat	Flat		X	390
Totals					3735

4.2 Participants Characteristics

The survey conducted by Metrix Matrix look at various participant-specific characteristics related with the participants. Almost 80 percent of the participants live in single-family homes. Similarly, 86 percent of the participants own their residence. Customers that own a house are more likely to make long-term investments in energy efficient appliances than the ones that live in the rented house (Stern, 1992). Electricity consumption also depends on the size of the customer's residence. Figure 2 shows a pie-chart according to the number of rooms in participants' residence. Almost half of the participants' residence has 6-8 rooms and 85% of the residences have less than 10 rooms.

The presence of energy-intensive appliances also determines the amount of residential electricity consumption. The magnitude of peak load reduction during critical peak events depends on the customers' ability and willingness to reduce or delay the use of energy-intensive appliances. Table 2 presents that status of ownership of energy intensive appliances among pilot study participants. The survey finds that only 4 percent of the customers have central air conditioning system at their residence, where as 61 percent have survey respondents have room air conditioning systems. Similarly, 65 percent have ceiling fans installed at their homes, 81 percent own clothes dryer, and 36 percent have dehumidifiers.

Figure 3-2: Number of Rooms per Household

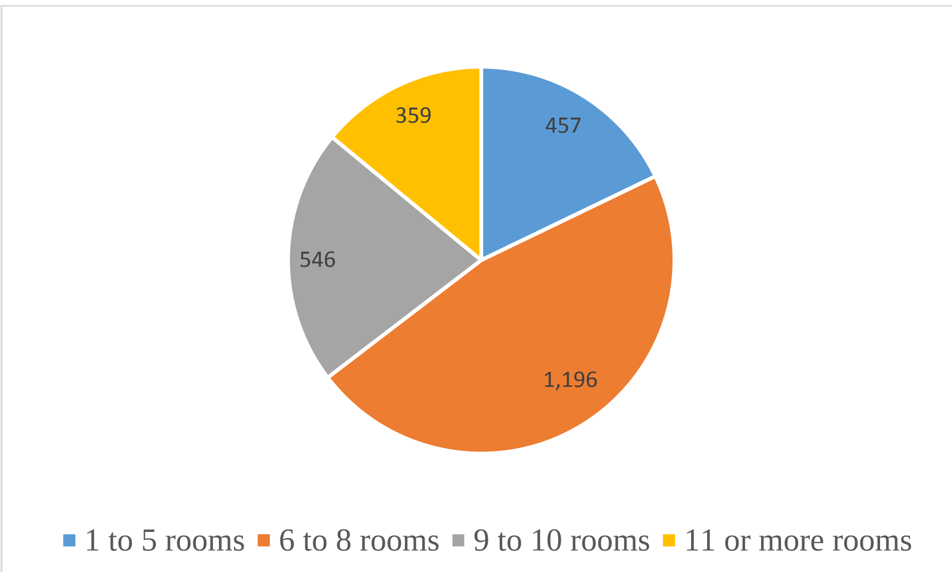


Table 3-2: Percentage of Household with different Appliances[33]

Applicances	*No (%)*	*Yes (%)*
Central AC	95.9	4.0
Programmable Theormostat for Central AC	58.3	37.1
Room AC	38.7	61.3
Ceiling Fans	34.3	65.6
Clothes Dryer	18.9	81.0
Dehumidifier	63.3	36.4

[33] The percentage may not add to 100 since it does not include participants that refused to answer or were not aware about possessing appliances.

The success of the critical peak events also depends on the participants' income and education levels. The participants' household income has an effect in their response during the critical peak events. Since the income elasticity of electricity demand is positive, customers with lower income may be more inclined to reduce electricity consumption during the critical peak events (Branch, 1993). Figure 3 shows household income distribution among the participants that responded to the survey questionnaire[34]. The figure shows that almost one-fourth of the participants have income level in $40,000 – $75,000 range and 44 percent of the households have an annual income of at least $40,000. Similarly, education level is also an important factor to the responses during the critical peak events. The rate structure, feedback information technology, and benefits from the critical peak events may be confusing. Figure 4 shows the customers' education level. The survey finds that 95 percent of the pilot study participants have at least high school degree and 57 percent of respondents have at least some college education.

[34] 19 percent of the survey respondents did not answer the question related with their household income.

Figure 3-3: Participants by household income

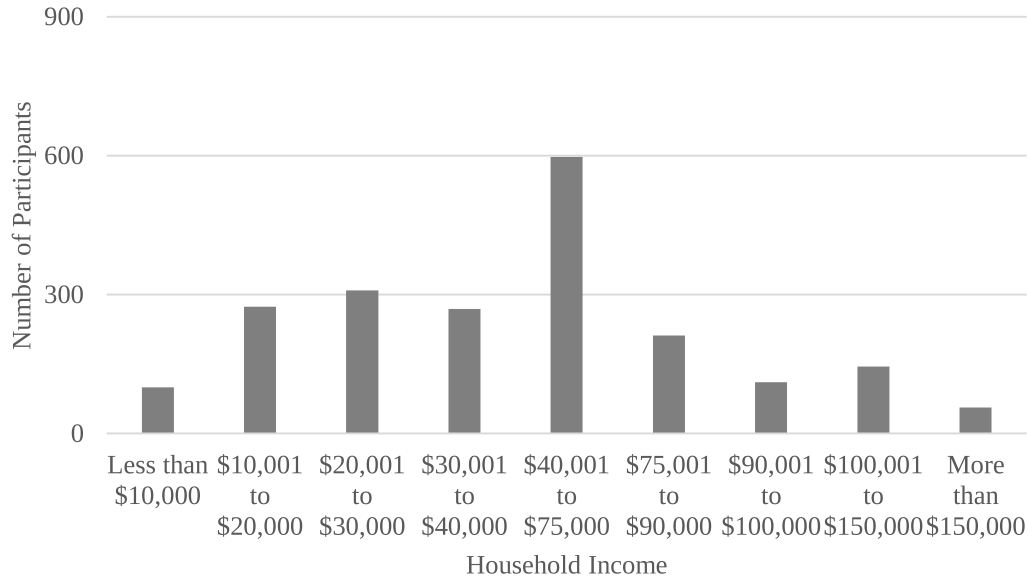
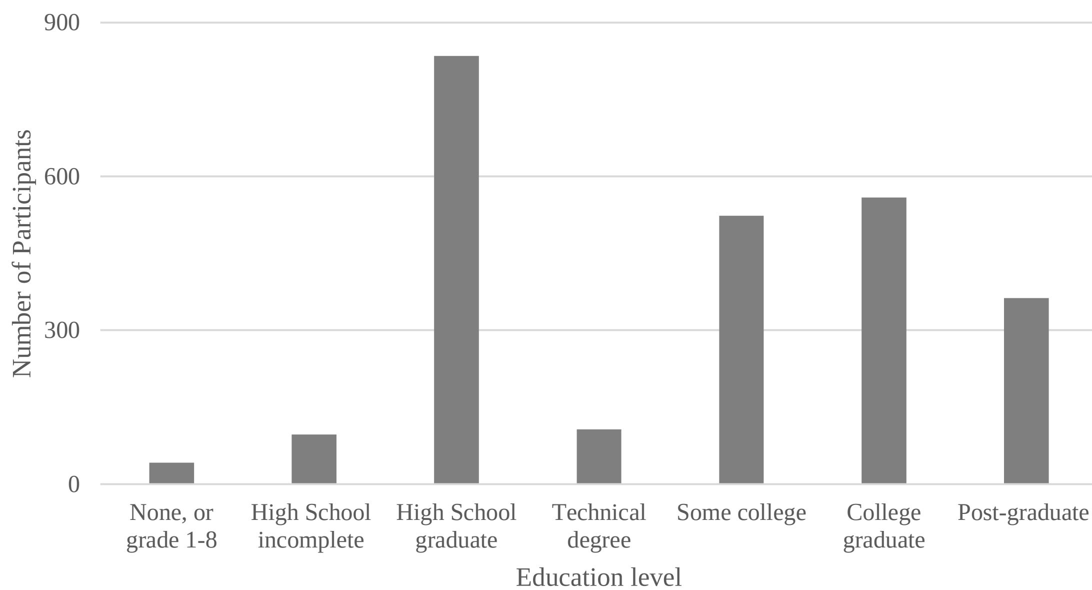


Figure 3-4: Participants by Education Level



4.3 Critical Peak Events

Green Mountain Power called four critical peak events in 2012 fall – September 14, 21, 25, and October 5 – from 1 pm to 6 pm.[35] In 2013, a total of ten events were called during the months of July and August. Critical peak events days of the second year are July 5, 15, 16, 17, 18, 19 and August 13, 21, 22, 28. Customers in the different treatment groups were informed about the events through email, text message, and/or automatic phone calls by 6 pm of preceding day of each critical peak event day. Table 3 gives the list of critical peak event days with the average temperature during event hours of the pilot study. The year 1 average temperatures during critical peak event hours range from 65.4 F to 77.8 F, whereas year 2 average temperature vary from 68.4 F to 90.0 F.

Table 3-3: Average temperature during five-hour of critical peak event hours

Event Date	*Temperarure (°F)*	*Heat Index (°F)*
9/14/12	77.8	75.7
9/21/12	69.2	66.9
9/25/12	65.4	62.6
10/5/12	70.4	68.2
7/5/13	86.4	83.5
7/15/13	87.8	84.7
7/16/13	86.4	83.6
7/17/13	89.0	85.7
7/18/13	87.0	84.1
7/19/13	90.0	86.6
8/13/13	68.4	66.2
8/21/13	82.2	79.8
8/22/13	82.0	79.6
8/28/13	82.4	80.0

[35] GMP could not call first year critical events during summer time mainly due to inability to distribute necessary technology in time.

4.4 Data

GMP collected 15-minute interval customer-level electricity usage data from March 2012, which is then aggregated at the hourly and monthly levels for the analysis. Besides electricity data, we also use hourly temperature data to control the possible change in the power consumption due to weather variations. Green Mountain Power with the help of Metrix Matrix surveyed participants, both before and after the pilot study. Customer-level survey data include pre-treatment demographic, household income, residential type, and other information. Survey data helps analyze the impact of various customer specific characteristics in the peak load reduction. Moreover, end of the program survey data assists in finding out customer's responses and satisfaction to the DR program.

5. **Theory**

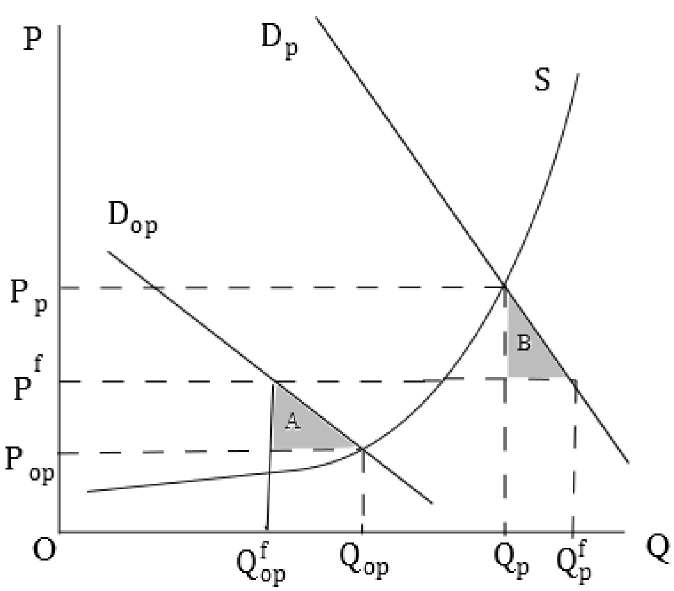
5.1 Motivation

This section briefly describes how incentive based DR programs change the electricity consumption pattern and affects the electricity price and social welfare. Demand side management (DSM) allows meeting demand during peak periods by increasing the flexibility to adjust end-users' power usage by responding to the change in electricity price. We start with discussing the impact of single retail electricity price in the welfare loss. In a regulated market, retail electricity price tend to be fixed whereas wholesale electricity price is dynamic reflecting generation cost and transmission congestion.

The demand of electricity and cost of generation varies with time. In low-demand period, low marginal cost plants may be sufficient to meet the demand. Whereas, utilities have to deploy high marginal cost plants during the peak demand period. Figure 5 shows the implication of having a fixed retail price. For simplicity, we divide into two periods – off-peak and peak. In a competitive market, the market clearing, equilibrium electricity prices would be P_{op} and P_p during off-peak and peak period, respectively. Let the regulated fixed retail electricity price be P^f where $P_{op} < P^f < P_p$.

At the fixed price of P^f , customers pay higher price during off-peak period, however they pay lower than willingness-to-pay price during the peak period. In the off-peak period, there is an excess supply of electricity equal to $\left(Q_{op} - Q_{op}^{f}\right)$ creating consumer welfare loss equal to the area A. Similarly, during the peak period, at the price of P^f, there is a shortage of electricity equal to the amount of $\left(Q_{\mathrm{p}}^{f} - \mathrm{Q_p}\right)$ resulting in the deadweight loss of area B. The electricity market experiences welfare loss in both off-peak and peak periods due to a single fixed electricity price. However, in case of electricity, in order to avoid blackouts and compromise grid reliability, there will be an excess generation as backup for peak period and are supplied to the grid if necessary. Since high demand periods last for a few hours of the day, these peaking and reserve plants do not operate full time resulting in inefficiencies.

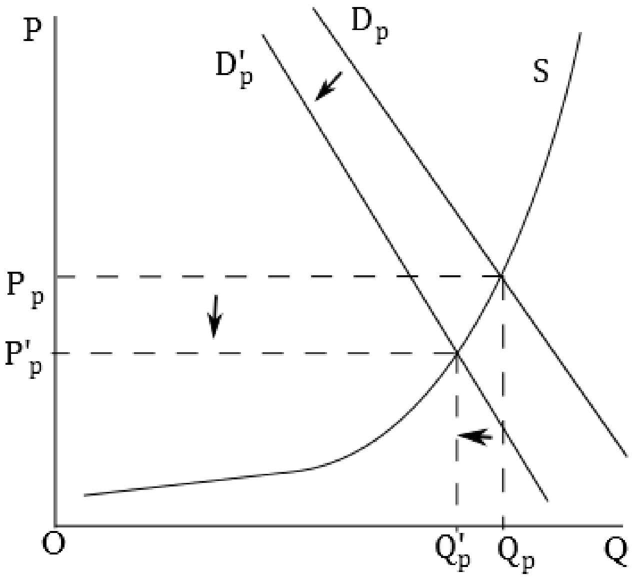
Figure 3-5: Impact of single-fixed electricity price in welfare loss



Dynamic retail pricing that reflects the real-time cost of generation and transmission constraints is the best way to get rid of efficiencies. However, real time pricing is a costly process – need infrastructures, interval meters, and two-way communication system – and it requires active customer engagement. Time-of-use (TOU) pricing is also another way to improve on constant electricity pricing model which charges fixed electricity price according to the time of the day. Critical peak events also known as emergency DR programs are also type of TOU pricing but are called only during very high electricity demand periods. Targeting very high demand period may be as effective as dynamic pricing in reducing the peak load and in avoiding cost required for upgrading the electricity infrastructures. In most power systems, top one percent of hours in the area are responsible for 10 percent of the peak load demand (Faruqui et al., 2010).

Now, we incorporate the impact of critical peak pricing on electricity demand and wholesale electricity price. As a result of very high pre-determined electricity prices, customers lower their electricity consumption during the event period resulting in the reduction of system peak load. In figure 6, CPP shifts system demand to the left resulting in the reduction of both wholesale electricity price and electricity demand. Due to the inelastic nature of electricity demand, the drop in wholesale electricity price is very large even with a small decrease in the demand of electricity.

Figure 3-6: Impact of shift in electricity demand in wholesale electricity price



The potential peak load reduction also benefits GMP by avoiding the cost required for new electricity infrastructures. The decrease in peak load in GMP area means that their share of cost associated with transmission upgrade and new investment in the New England ISO region will decrease. The cost of new transmission investment that provides regional benefits is shared among the NE-ISO states. This cost sharing is proportional to the percent of each state's electricity demand to the total demand within the NE-ISO region. Vermont, being the smallest state in terms of electricity consumption, is responsible for 4.1 percent of the total cost. Considering that transmission upgrade and investment costs are substantial and GMP being the sole investor owned utility company serving 80 percent of Vermonters, the share of GMP can be substantial. Thus reducing peak load reduction through DR programs allows GMP to reduce their share of upgrade and new investment costs.

5.2 Peak Load Change Analysis

The main objective of the study is to estimate the potential peak load reduction due to emergency DR programs in Rutland, VT. We use difference-in-difference regression approach using two separate models. We start with Randomized Control Treatment (RCT) analysis followed by Randomized Encouragement Design (RED). We prefer results from RCT analysis if both models give comparable results because RCT produces an unbiased estimate with the smallest amount of variance per affected customers.

5.2.1 RCT Analysis

In a randomized control treatment study, eligible group of customers are randomly assigned to various treatment and control groups. The difference-in-difference regression model for RCT analysis is presented in equation (1).

$$(1)\quad y_{it} = \beta_i + \beta_1\, Temp_t + \beta_2 \sum_j DT_{ji} + \beta_3^{DB} DB_t + \beta_3^{DE} DE_t + \beta_3^{DA} DA_t + \beta_4^{DB} \sum_j DT_{ji} * DB_t + \beta_4^{DE} \sum_j DT_{ji} * DE_t + \beta_4^{DA} \sum_j DT_{ji} * DA_t + \varepsilon_{it}$$

where *i*, *j*, and *t* indices for household, treatment groups, and hour number respectively. y is the residents' hourly electricity consumption. $Temp$ includes three weather related hourly variables – heat index[36], cooling degree hours[37], and cumulative cooling degree hours[38]. DT indicates the variable that represents different treatment rates of the emergency DR study. DB, DE, and DA

[36]Heat index is "apparent temperature" or the temperature after taking into account of the humidity. It is calculated with the formula of $HI = \mathrm{c}_1 + \mathrm{c}_2\mathrm{T} + \mathrm{c}_3\mathrm{R} + \mathrm{c}_4\mathrm{T} * \mathrm{R} + \mathrm{c}_5\mathrm{T}^2 + \mathrm{c}_6\mathrm{R}^2 + \mathrm{c}_7\mathrm{T}^2 * \mathrm{R} + \mathrm{c}_8\mathrm{T} * \mathrm{R}^2 + \mathrm{c}_9\mathrm{T}^2 * \mathrm{R}^2$ where T is temperature and R is the relative humidity with c_1= -42.397, c_2 = 2.049, c_3= 10.143, c_4= -0.2247, c_5= -6.838*10^{-3}, c_6= -5.482*10^{-2}, c_7= 1.228*10^{-3}, c_8= 8.528*10^{-4}, and c_9= -1.99*10^{-6}

[37] Cooling degree hours are measure of how much (in degrees) is outside temperature higher than the base temperature, here 65 degree F. Mathematically, cooling degree hours = maximum(temperature – 65, 0).

[38] Cumulative cooling degree (CCD) is the sum of total cooling degrees in a day.

are three binary variables denoting hours surrounding critical peak event – before, during, and after the event, respectively. The indicator variables are for the six-hour period leading up to the start of an event, five-hour event period, and the 24-hour period following the conclusion of the event. ε is the error term.

The treatment parameter β_2 gives the mean difference in hourly load consumption between treatment group j and control with no-notification group. Similarly, coefficient β_3 estimates the impact of critical peak events in hourly load consumption. The primary interest of this paper is to estimate β_4 which gives the mean differences of hourly loads between various treatment groups with the control-no-notification group during the critical events.

Although GMP structured the DR study to be randomized, there were customers that declined to participate when approached during the recruitment process and few other customers dropped out[39] during the period of the pilot study. Paper uses randomized encouragement design (RED) analysis to take into account the participants that declined to participate or dropped out during the study.

5.2.2 RED analysis[40]

For RED analysis, even though participants are assigned to different groups randomly, we treat costumers as if they were encouraged to take one of the treatments. In our analysis, all

[39] Most of the dropped out customers are from CPP treatment group. CPR participants can simply opt-out of the study by ignoring the critical peak events.

[40] RED analysis is only performed for participants that face CPP rates. CPR customers pay a fixed normal electricity rate during the peak events and only get financial incentives if they decrease the consumption. Even if CPR customers that are not excited about participating in the program, they might still be a part of the program and not respond during the peak events since the participation is voluntary.

customers who were recruited into a particular treatment are treated as if they were "encouraged" to adopt the treatment. Since the vast majority of customers who exited the study did so during the initial survey contact (before actually being put on their rate and/or information treatment) we group those customers together with the few customers who dropped out after actually being put on their rate and/or information treatment. We note that drop-out (as opposed to customers declining to participate) came from the CPP groups; customers could effectively drop out of the CPR treatment by simply ignoring the notifications. Given our data we are not able to identify specific customers who have dropped out of the CPR treatment.

The RED analysis for customers in CPP and CPP with IHD groups proceeds in two stages. The first stage regression predicts the proportion of customers in each treatment groups who adopted the treatment. The second stage is similar to RCT analysis except the indicators used for denoting critical event hours. Instead of a binary variable, we use the predicted values calculated in the first stage, equation 2.

$$(2) \quad T_{Aj} * DE = \sigma_j + \sigma_1 \left(T_{Ej} * DE\right) + \sigma_2 \, DE + e_{it}$$

$$(3) \quad y_{it} = \beta_i + \beta_1 \, Temp_t + \beta_2 \sum_j DT_{ji} + \beta_3^{DB} \sum_k DB_{ki} + \beta_3^{DE} \sum_k \widehat{DE}_{ki} + \beta_3^{DA} \sum_k DA_{ki} + \beta_4^{DB} \sum_j \sum_k DT_{ji} * DB_{ki} + \beta_4^{DE} \sum_j \sum_k DT_{ji} * \widehat{DE}_{ki} + \varepsilon_{it}$$

where, in equation (3), T_{Aj} is the binary variable that indicates the set of customers in the accepted group. Similarly, the dummy variable T_{Ej} consists participants that are in the encouraged group[41]. $\widehat{DE}$ is the predicted value from calculated from the first stage regression.

[41] Please note that the majority customers declined to participate during the recruitment process, not during the period of the study, thus the set of customers in both encouraged and accepted groups remain same for all the critical events of the first year study.

5.3 Persistence Analysis

The paper analyzes the change in customers' electricity usage as more critical events are called. The persistence analysis is important to find how customers behave in the long-term. The analysis specifically looks at three different time horizons – within critical event period, across critical events, and between year 1 and year 2. The study of participants' responses at different time horizons along the critical peak events is important for planning purposes.

Equation (4) estimates the within-event persistence analysis where we look at the hourly electricity consumption during the critical peak event.

$$(4)\quad y_{it} = \alpha_i + \alpha_1 HI_t + \alpha_2\, DE * \sum_t H_t * HI_t + \alpha_3\, DE * \sum_j \sum_t DT_{ji} * H_t * HI_t + \varepsilon_{it}$$

where HI indicates the heat index[42], H is the hour of the day. The coefficient α_2 estimates the temperature controlled hourly change in electricity consumption in each hours within the critical peak event. Similarly, α_3 predicts the hourly change in customers' electric load by treatment groups across the event period.

The paper uses equation (5) to determine event-to-event persistence effects on the hourly load consumption. The response of participants, as a function of number of events called, is important to analyze if the behavior is consistent across the events.

$$(5)\quad y_{it} = \mu_i + \mu_1\, HI_t + \mu_2 \sum_k DE_{ki} + \mu_3 \sum_k DE_{ki} * HI_t + \mu_4 \sum_j \sum_k DT_{ji} * DE_{ki} * HI_t + \varepsilon_{it}$$

[42] For persistence analysis, we only use heat index to control for weather.

In equation (5), k denotes critical peak events. The parameter μ_3 estimates the temperature controlled hourly load change in different critical peak events. Whereas, μ_4 estimates the impact in hourly electricity consumption by each treatment group.

The paper also looks at the impact of critical peak events on inter-year electricity usage. However due to the lack of long-term data since the pilot study lasts only for two years, our year-to-year persistence analysis may be limited.

$$(6) \quad y_{it} = \gamma_i + \gamma_1 HI_t + \gamma_2\, year2 + \gamma_3 DE * year2 + \gamma_4\, DE * year2 * \sum_j DT_{ji} + \varepsilon_{it}$$

where $year2$ is a binary variable indicating year of the study, 1 if the data belongs to second year and 0 otherwise. We do not differentiate across critical events since our purpose is to predict how participants behaved between first and second years of the study. The parameter γ_3 predicts the mean differences of potential peak load reduction due to critical peak events between year 1 and year 2. The coefficient γ_4 gives the change in hourly electric load between first and second years by treatment groups.

5.4 Energy Consumption Analysis

Besides estimating the potential peak load reduction during critical peak events, we also analyze the impact of real time electricity feedback system on energy consumption. Customers equipped with the IHD technology can look at their real time electricity usage and can adjust their consumption pattern. The analysis compares monthly electricity usage for customers before and after the installation of feedback technology. The customers received the IHD technology during the month of August 2012. We define pre-IHD period from March 2012 – July 2012, while IHD period is defined as August 2012 to December 2012.

We use difference-in-difference regression with household fixed effects and month fixed effects to estimate the impact of IHD in monthly electricity usage. The specification also controls for the weather.

$$(7) \quad y_{im} = \theta_i + \theta_m + \theta_1 W_m + \theta_2\, IHD + \varepsilon_{im}$$

where *m* indexes month. θ_i is the customer-fixed effects, whereas θ_m denotes the month-fixed effects. *W* contains weather related variables – average heat index and average number of cooling degrees in a month. *IHD* is an indicator variable identifying those customers with the real-time electricity feedback system. *IHD* takes a value of 1 for customers that are in the CPR and CPP groups and equipped with in-home-display units. The feedback information systems were delivered to customers before critical peak events of August 2012, thus *IHD* takes the value of 0 all the observations before August 2012. The parameter of interest is θ_2 which gives the average change in monthly electricity usage between customers that have IHD equipment installed at their house and those that do not.

6. Descriptive Statistics

The two-year study consists of 28.13 million hourly observations of 2507 unique customers, divided into four treatment groups and two control groups. [43] Tables 4 and 5 give summary statistics of different treatment groups during year 2012 and 2013. Further, we

[43] Please note that CPR-CPP group customers were in CPR rate structure in year 1 and were unaware of the change in their rate structure in the second year. So, we include them with CPR group in first year analysis. Similarly, CPR-CPP-IHD customers are in the CPR-IHD category. Number of participants in four treatment rates – CPR, CPR-IHD, CPP, and CPP-IHD are 809, 332, 445, and 167 respectively. The reason of higher number of participants in CPR and CPR-IHD groups than the other two is due to the inclusion of CPR-CPP and CPR-CPP-IHD group customers in CPR and CPR-IHD during the first year.

calculate descriptive statistics of hourly electricity usage including only weekdays and critical event hours. The average hourly load of participating customers during first year of the study is 0.82 kW with the standard deviation of 0.88 kW. The average hourly weekday consumption is 0.81 kW with the standard deviation of 0.86 kW. During the critical peak event hours of first year, the average hourly load consumption across the participants is 0.68 kWh.

The average hourly electricity consumptions across treatment groups, during the first year's critical peak event hours, range from 0.61 kWh to 0.72 kWh. The descriptive statistics suggest that, during the critical peak hours, the average hourly consumption for all treatment groups is lower than that of the control group. Among four treatment rates, participants in the CPP rate with in-home-display technology have the minimum average hourly consumption of 0.61 kWh whereas only control group customers have maximum hourly usage of 0.72 kWh.

Table 3-4: Descriptive statistics, and summary of treatments, for the Year 1.

Group	*Number of Customers*	*No. Obs ('000)*	*Mean (kWh)*	*SD (kWh)*
a) All Hours				
CPR	809	5605.42	0.84	0.91
CPR-IHD	332	2318.63	0.79	0.85
CPP	445	3023.33	0.81	0.85
CPP - IHD	167	1156.59	0.79	0.86
CTRL	354	2497.36	0.81	0.87
CTRL - N	400	2784.69	0.83	0.91
Total	*2507*	17386.00	*0.82*	*0.88*
b) Weekday Hours				
CPR	809	4010.44	0.83	0.89
CPR-IHD	332	1659.05	0.78	0.83
CPP	445	2164.29	0.80	0.84
CPP - IHD	167	828.05	0.78	0.85
CTRL	354	1786.91	0.80	0.85
CTRL - N	400	1992.14	0.82	0.85
Total	*2507*	12440.88	*0.81*	*0.86*
c) Critical Peak Event Hours				
CPR	809	16.02	0.69	0.76
CPR-IHD	332	6.64	0.65	0.75
CPP	445	8.80	0.66	0.71
CPP - IHD	167	3.31	0.61	0.67
CTRL	354	7.06	0.72	0.78
CTRL - N	400	8.00	0.72	0.74
Total	*2507*	*49.8*	*0.68*	*0.74*

Table 3-5: Descriptive statistics, and summary of treatments, for the Year 2.

Treatment Groups	*No of Observations*	*Mean (kWh)*	*SD (kWh)*
a) All Hours			
CPR	2360.91	0.80	0.87
CPR-IHD	1208.45	0.79	0.86
CPP	2961.52	0.80	0.85
CPP-IHD	1484.92	0.79	0.95
CTRL	2009.44	0.81	0.88
CTRL-N	1952.21	0.80	0.83
Total	12581.72	*0.80*	*0.88*
b) Weekday Hours			
CPR	1684.73	0.80	0.86
CPR-IHD	862.37	0.78	0.85
CPP	2108.20	0.79	0.83
CPP-IHD	1056.93	0.78	0.84
CTRL	1433.87	0.80	0.86
CTRL-N	1393.19	0.79	0.82
Total	8977.56	*0.79*	*0.85*
c) Critical Peak Event Hours			
CPR	19.71	1.20	1.20
CPR-IHD	10.13	1.13	1.11
CPP	26.01	1.14	1.14
CPP-IHD	13.03	1.06	0.98
CTRL	17.09	1.20	1.16
CTRL-N	16.52	1.13	1.00
Total	106.08	*1.15*	*1.14*

Table 3-6: Number of unique customers by group

Group	*Year 2012*	*Year 2013*
CPR	809	433
CPR-IHD	332	223
CPP	445	603
CPP-IHD	167	307
Control - no notification	354	353
Control - notification	400	350

The distinction of hourly load usage among treatment groups is more apparent in figures 7 – 10 where we plot hourly average kW consumption, as well as differences between load profiles between treatment and control groups, across all event days. Figures 7 and 8 contain hourly load profiles for IHD and no-IHD customers, respectively, for 2012. Similarly, figures 9 and 10 represent average load profiles of 2013 event days. The upper set of curves represents levels of consumption, while the lower set represents the difference between the treatment and control groups. The shaded part in the figure indicates the five-hour critical event.

Figure 7 shows the average hourly load of IHD customers facing both treatment rates and control-with-no-notification group during 2012 event days. The figure 7 shows that all three groups of customers follow similar load patterns during the hours surrounding the critical peak events. It also suggests that the average hourly load of both CPP-IHD and CPR-IHD customers are lower than control groups' average hourly load during the event hours. Similarly, the figure 8 shows the average hourly electricity consumption of no IHD and control groups for 2012. Comparing figures 7 and 8, we see that the customers in critical peak pricing with IHD rate reduced maximum as compared with the control with no-notification group during the event hours. Moreover, the differences in both figures show that, both during event and non-event hours, the electricity usage of customers with IHD technology is lower than the no-notification control group and treatment groups without IHDs.

Figure 3-7: Average hourly load of IHD groups and no-notification control group during critical peak events of 2012

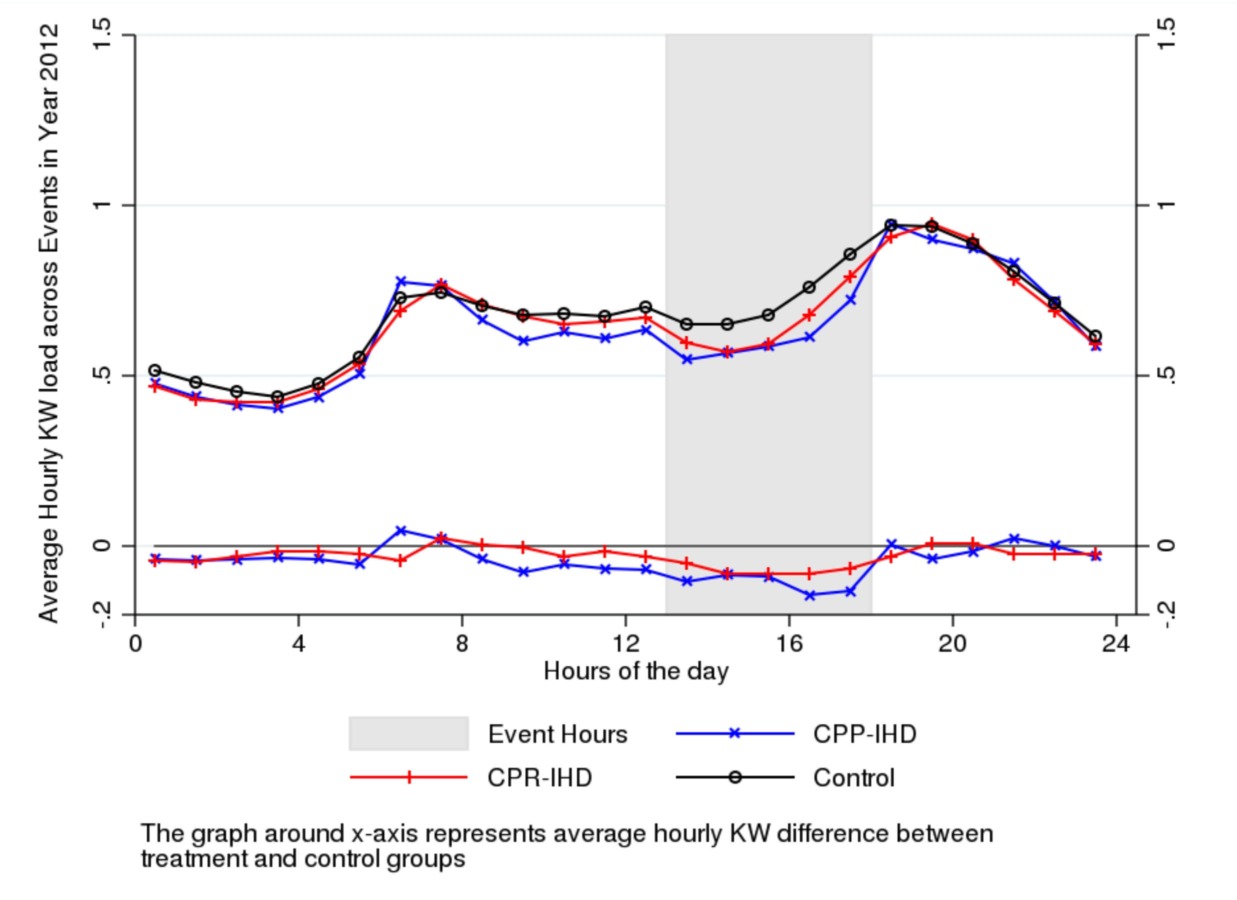
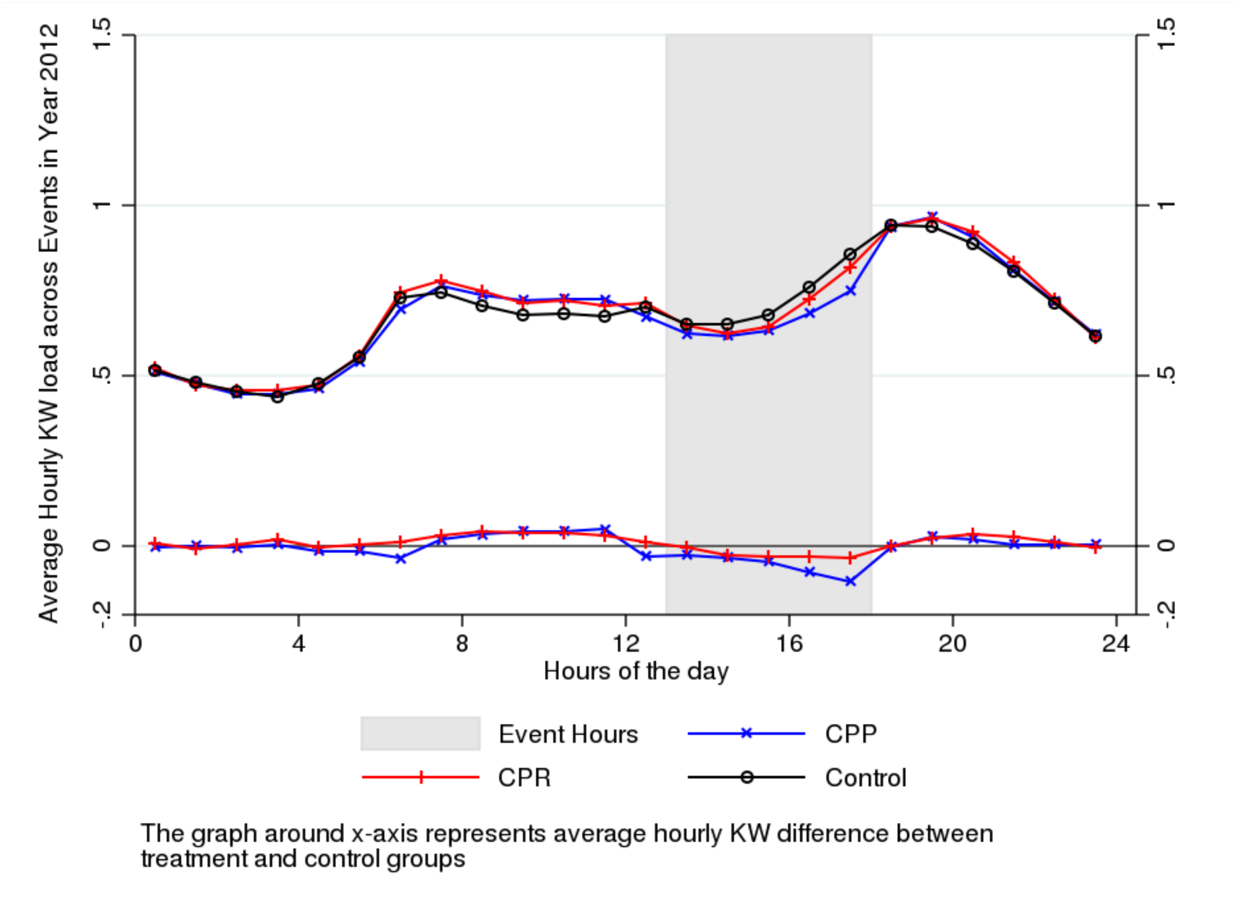


Figure 3-8: Average hourly load of no-IHD groups and no-notification control group during critical peak events of 2012



The average hourly electricity consumption of 2013 event days, figures 9 and 10, also tell similar story. The customers in rate and technology treatment groups are responding during the declared critical peak events. Treatment group customers' electricity consumption is lower than that of the control group customers. Response of customers with the information treatment is greater than the customers that do not possess the technology. Figures 7 – 10 also show the distinction between IHD and non-IHD customers' electricity consumption before the start of the critical peak events. As preemptive measure, customers with IHD technology reduce consumption, as compared with the control group customers, before the start of the events.

Whereas, the average hourly load shows that treatment group customers without IHD technology consume more electricity during the same period.

Figure 3-9: Average hourly load of IHD groups and no-notification control group during critical peak events of 2013

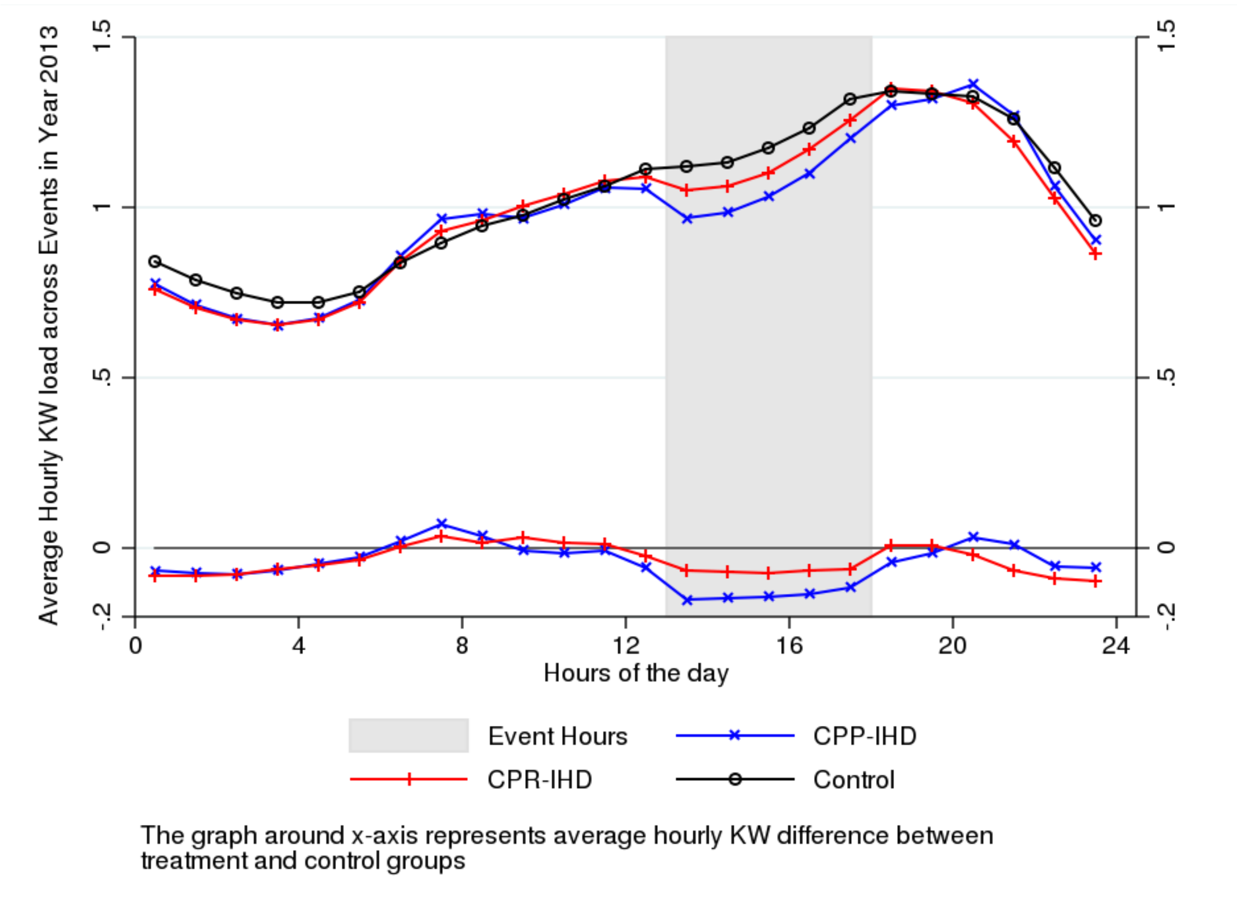
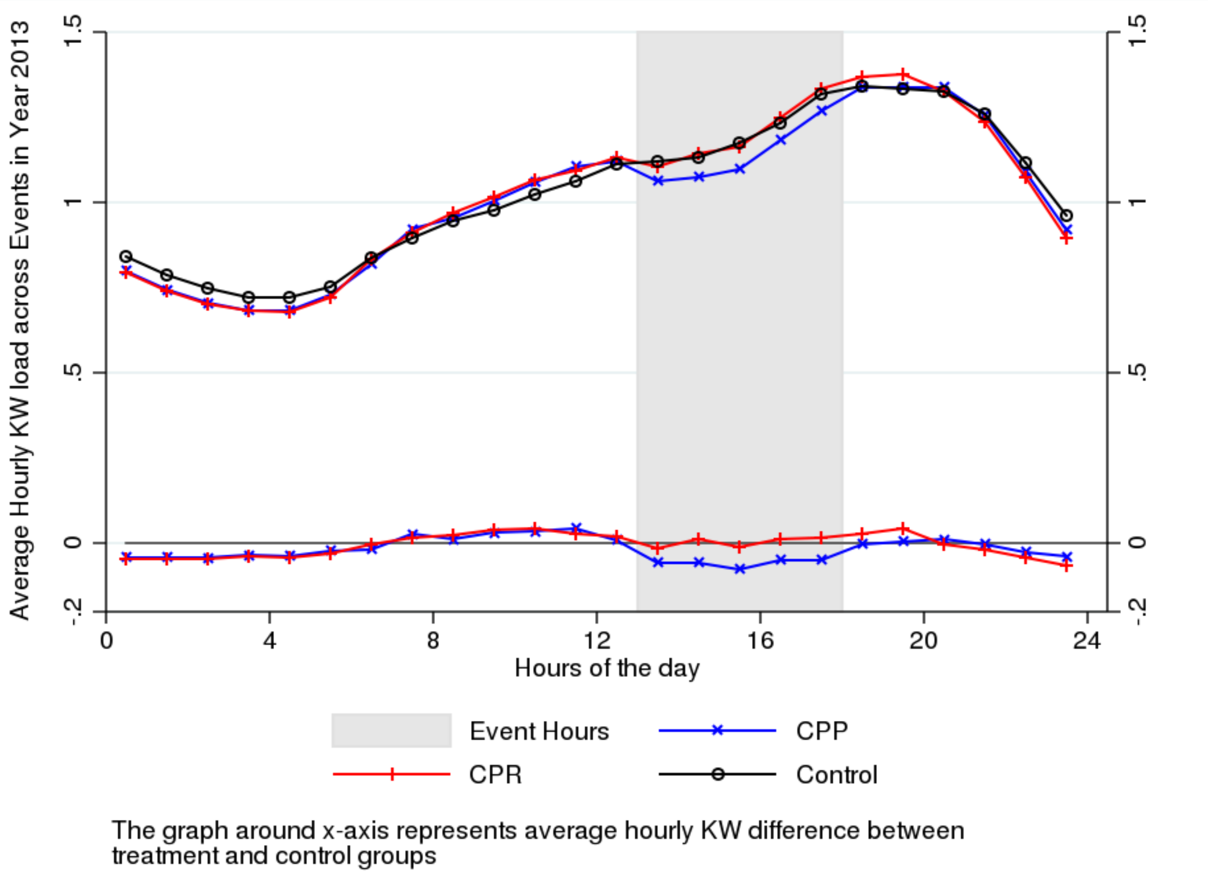
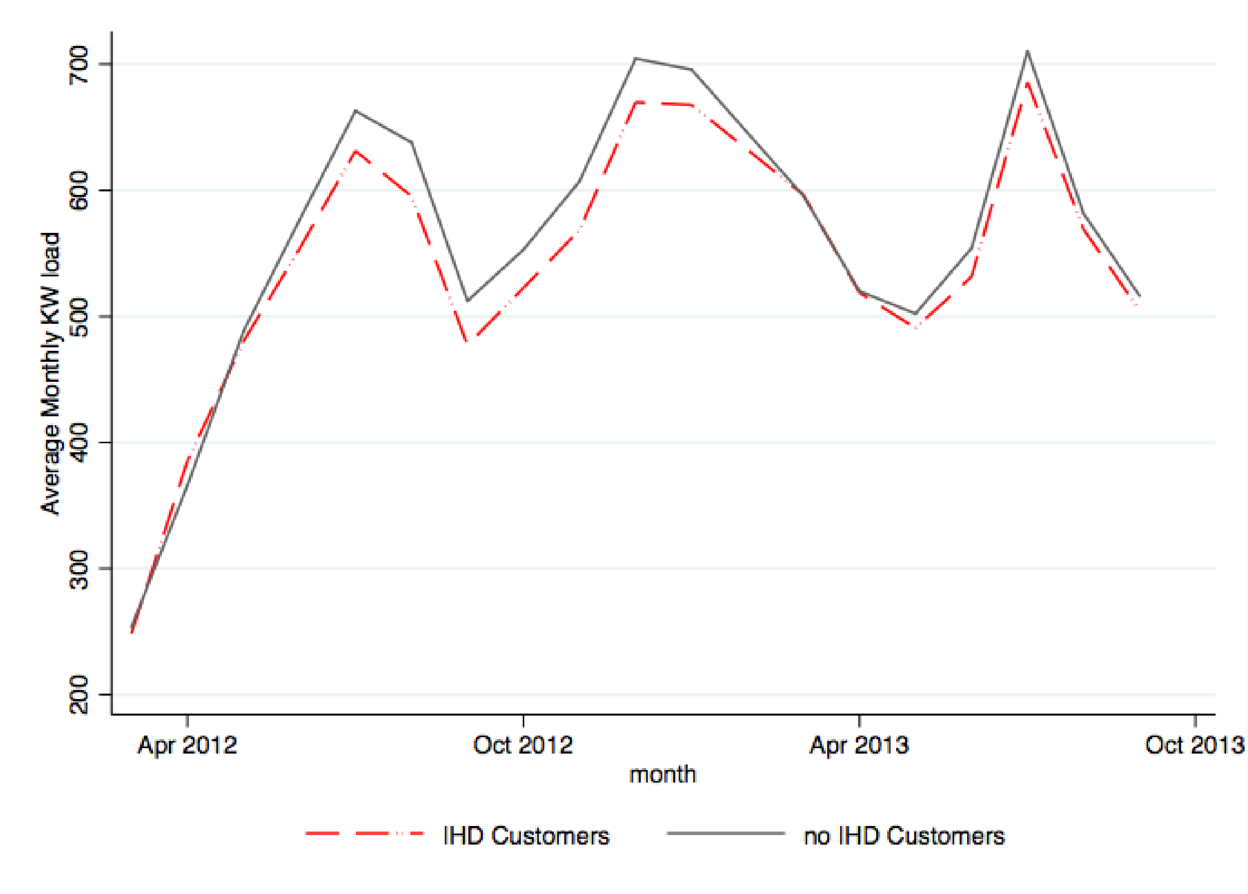


Figure 3-10: Average hourly load of no-IHD groups and no-notification control group during critical peak events of 2013



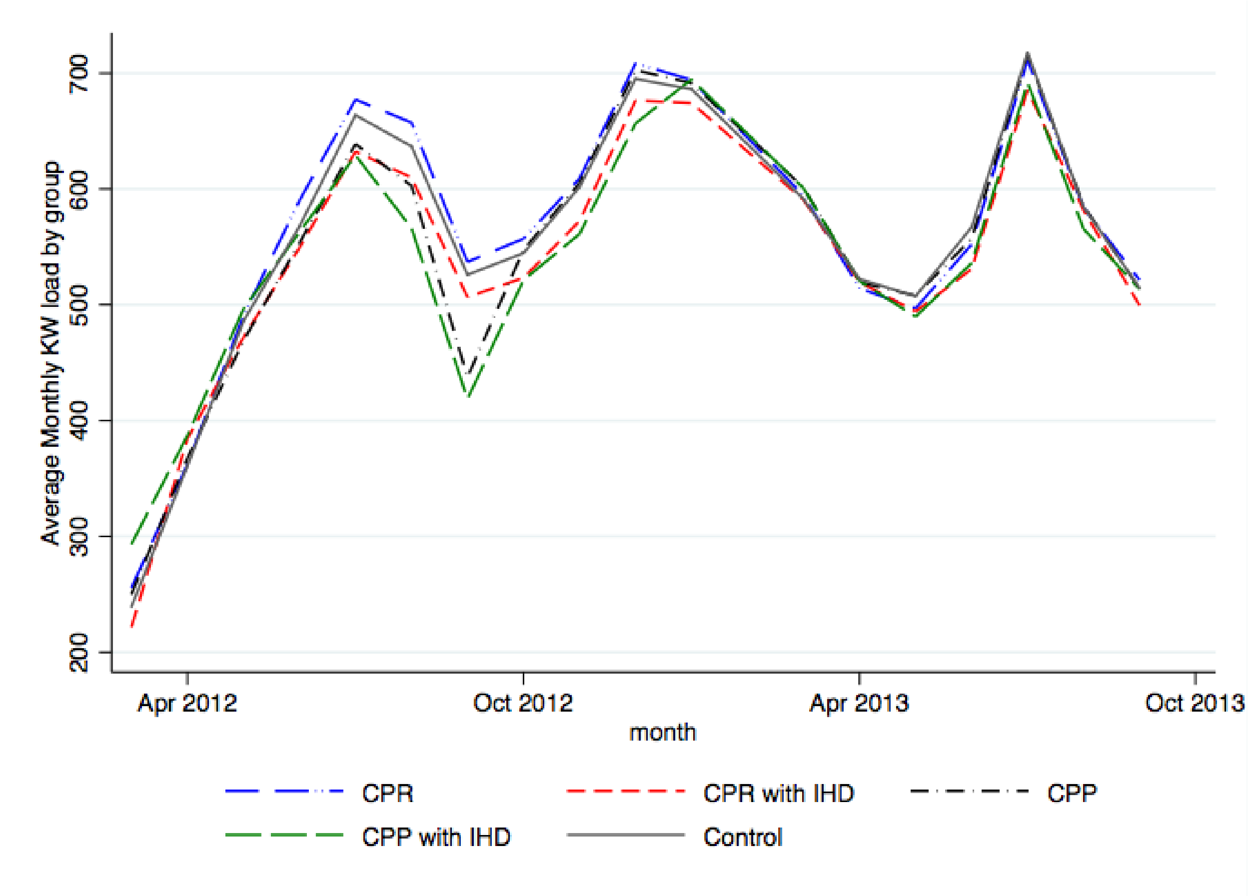
The paper also looks at the impact of feedback technology in the electricity usage of participants during non-event hours. Figure 11 gives the average monthly electricity usage of IHD and no-IHD customers. The monthly electric load figures follow similar pattern highlighting the homogeneous response of the customers to weather patterns and other dynamic characteristics. However, the figure also shows that the daily electricity consumption of IHD customers is always lower than no-IHD customers. The difference in average monthly electricity usage between IHD and no-IHD groups may suggest the impact of IHD technology that allows customers to continuously monitor their real-time electricity usage.

Figure 3-11: Average monthly KW load for customers with and without in-home-display (IHD) systems



Moreover, figure 12 presents average monthly load (kW) by treatment groups. The monthly load patterns of various treatments are very similar. The monthly load consumption of CPP and CPP-IHD customers are lower during the month of August 2012 as compared with CPR and control group customers. It might be because of the change in their consumption behavior after installing IHD equipment. However, this behavior fades away after few weeks.

Figure 3-12: Average monthly KW load for customers by treatment group



7. Result and Analysis

This section presents the regression results analyzing the consumers' behavior due to the critical peak events. We start with estimating the potential peak load reduction at different time periods surrounding the critical event period with the help of RCT approach. Then, we conduct RED analysis in order to incorporate CPP customers that declined to participate in the pilot study. Tables 7 and 8 present regression results from RCT and RED analyses, respectively. Similarly, the paper includes the regression results, tables 9 – 11, from persistence analysis conducted at three different time horizons – within critical peak events, event-to-event, and year-to-year. We also estimate the impact of continuous feedback technology in the monthly electricity consumption. All the models include customer-level fixed effects. Standard errors are robust and clustered at the customer-level to control for the serial correlation.

7.1 Peak Load Analysis

7.1.1 RCT and RED Analysis

The regression results from table 7 show that customers hourly load reduction during the critical peak period is statistically significant. Pilot study participants of Rutland, VT decreased 0.034 kW per hour on average as compared with control with no-notification customers during the five-hour critical peak event period. Similarly, during the six-hour prior to the events called and 24-hour after the event, the hourly consumption of electricity were higher as compared with the control with no-notification group customers. On average, treatment group participants increased electricity usage by 0.069 kW and 0.147 kW than the control group participants during the pre- and post-event periods respectively.

The study's primary interest is to predict the impact of different treatment and information rates in real-time electricity usage. The coefficient estimates of interaction variables between critical event hours and treatment groups, β_3 in equation 1, show that customers in different rates responded distinctly. On average, residents on CPR treatments decreased hourly load by 0.045 kW and CPR customers equipped with IHD reduced 0.068 kW of hourly load. The log-linear econometric model suggests that CPR group customers' peak load reduction is 5.5 – 6.8 percent higher than the control group customers. The response of CPP treatments customers is larger than the CPR customers. Customers in the CPP rate reduced hourly electric usage by 0.051 kW during the event period. The maximum hourly load reduction is seen among CPP customers with IHD technology. On average, CPP with IHD customers decreased 0.103 kW of electric load per hour, 8.5 percent more than control group customers, during the critical peak events of the first year of the study. Please note that, responses of CPR-IHD and CPP-IHD group customers are only statistically significant among the responses of different treatment groups.

The paper also examines the impact of treatment rates during the periods surrounding the critical events. The results show that there is no statistical significant difference in hourly load usage between treatment and control group customers during both periods - six-hour window preceding the start of the event and 6 hours after the end of the event.

The RED analysis results are presented in table 8. The analysis, taking CPP customers that declined to participate or dropped out during the study into account, shows that the hourly load reduction by CPP customer is larger than the one predicted by RCT analysis. On average, CPP customers decreased 0.116 kW of electric load per hour, which is 1.12 times larger than predicted by the RCT approach. During the first year of the study, 155 participants in critical peak treatment rate, in which 113 customers are in CPP group (25.4 % of the total CPP treatment group) and 37 residents belong to CPP with IHD customers (22.1 % of the CPP-IHD group), declined to participate after the treatment groups were revealed to them. Similarly, during the period of the second year, 37 CPP customers (11.5 %) and 21 CPP-IHD customers (12.2 %) dropped out of the pilot study.

The second way to account customers that declined to participate or dropped out of the program is with the help of local average effect (LATE) method. In this method, we divide the estimates of RCT analysis by the difference in the fraction of customers who took up the rate between the encouraged group and the non-encouraged group. The accepted percentage for CPP and CPP-IHD groups are 80.75% and 82.89%, respectively. The coefficients of CPP and CPP-IHD customers during critical peak event hours are comparable across three different methods.

LATE method suggests that CPP treatment group customers reduced 0.0630 kW as compared with the control group customers during event hours. Similarly, CPP with IHD customers' reduction is 0.125 kW during the same period.

Table 3-7: Regression Results for Randomized Control Treatment Analysis

Treatment Groups	*Only Group*	*Interaction of Group*Events*		
		DB	*DE*	*DA*
		0.069***	-0.034	0.147***
		(0.016)	(0.023)	(0.019)
CPR	0.025	-0.006	-0.045	-0.032
	(0.022)	(0.021)	(0.031)	(0.026)
CPR with IHD	-0.013	0.006	-0.068*	-0.028
	(0.025)	(0.027)	(0.036)	(0.030)
CPP	-0.013	0.033	-0.051	0.002
	(0.023)	(0.022)	(0.031)	(0.026)
CPP with IHD	-0.017	0.024	-0.103***	0.010
	(0.026)	(0.027)	(0.036)	(0.031)
Control with notification	0.011	-0.025	-0.053*	-0.032
	(0.008)	(0.023)	(0.032)	(0.027)
Number of observations		*26,378,106*		

*note: *** p<0.01, ** p<0.05, * p<0.1*

Table 3-8: Comparing coefficient estimates of CPP and CPP-IHD customers with RCT, RED, and LATE methods

Independent Variables	*RCT Analysis*	*RED Analysis*	*LATE Analysis*
Before Event Hours * CPP	0.033	0.038	0.0406
	(0.022)	-(0.026)	(0.028)
Before Event Hours * CPP - IHD	0.024	0.027	0.0285
	(0.027)	-(0.030)	(0.032)
During Event Hours * CPP	-0.051	-0.058	-0.0632
	(0.031)	-(0.036)	(0.039)
During Event Hours * CPP - IHD	-0.103***	-0.116***	-0.1247
	(0.036)	-(0.040)	(0.043)
After Event Hours * CPP	0.002	0.002	0.0021
	(0.026)	-(0.030)	(0.032)
After Event Hours * CPP - IHD	0.010	0.011	0.0118
	(0.031)	-(0.035)	(0.038)

7.2 Persistence Analysis

The goal of persistence analysis is to estimate consumers' electric usage pattern during different time-horizons within the period of the study. Table 9 presents the persistence analysis within different hours of the critical event periods. Similarly, event-to-event consumption analysis is presented in table 10. And table 11 contains the regression results of year-to-year persistence analysis.

The paper looks at the participants' hourly response during the critical peak events through hour-to-hour persistence analysis. The regression results are presented in table 9. The interest of this analysis is to compare the customers' hourly electricity usage during the critical peak events. With the help of regression analysis, we predict the coefficient associated with the interaction of critical peak event indicator with the hour dummy variables. The coefficient, α_2 in equation (4), gives the mean hourly differences of electricity consumption with the average consumption from 12 – 1 pm of critical event days. Moreover, in order to control for the temperature variations, we interact hour and event indicators with the hourly heat index.

The responses in residential power consumption during all event hours are statistically significant. The result suggests that treatment-group customers hourly consumption increased by 0.030 – 0.036 kW with a degree increase in heat index during event hours as compared with the control group customers. The more important result is the responses of different treatment groups during event hours.

We look at each treatment groups' electricity usages during the critical peak event hours. The treatment indictor variables are interacted with hourly heat index to control for the possible variations in electricity consumption due to the temperature change. The results of different treatment rates show that the responses are consistent across different hours during the event. This result is very encouraging for utility company because customers' electricity usage behavior does not die out during the event. We find that, even when we account for weather conditions, customers in all four-treatment groups reduced electricity consumption during the event hours. Any variations in persistence of response are small, amounting to 0.001 kW or less. This may suggest that consumers are not micro-managing electricity consumption during peak events, but rather are taking actions at a single point in time (such as adjusting thermostat settings) that would ultimately lower their consumption levels during critical peak events.

Table 3-9: Persistence Analysis: Within Event Hours

Independent Variables	*Hour 13*	*Hour 14*	*Hour 15*	*Hour 16*	*Hour 17*
Hour * Event-hour Indicator * heat index	0.030***	0.034***	0.038***	0.036***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
*Group * Hour * Event-hour indicators * heat index interaction terms*					
CPR	-0.001***	-0.001**	-0.001***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CPR with IHD	-0.001**	-0.002***	-0.002***	-0.001***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CPP	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CPP with IHD	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No of Observations			26,427,323		

*note: *** p<0.01, ** p<0.05, * p<0.1*

Table 10 and figure 13 present the regression results of event-to-event persistence analysis. Table 10 uses data for 2012 events, while figure 13 shows the change in hourly usage due to planned critical events of 2013. The regression model uses heat index to control for possible change in electricity consumption due to the weather variations. The results show that customers’ reaction to the first and third critical peak events of 2012 were greater than the other two events. On average, treatment group customers on critical peak event of September 14, 2012 reduced hourly load consumption by 2.288 kW as compared with the control with no-notification customer group. Similarly, the decrease in hourly electricity consumption during September 25, 2012 is 2.362 kW. However, treatment group customers during critical peak events of 21 September, 2012 and 5 October, 2012 showed lower reduction, 0.777 kW and 0.916 kW respectively.

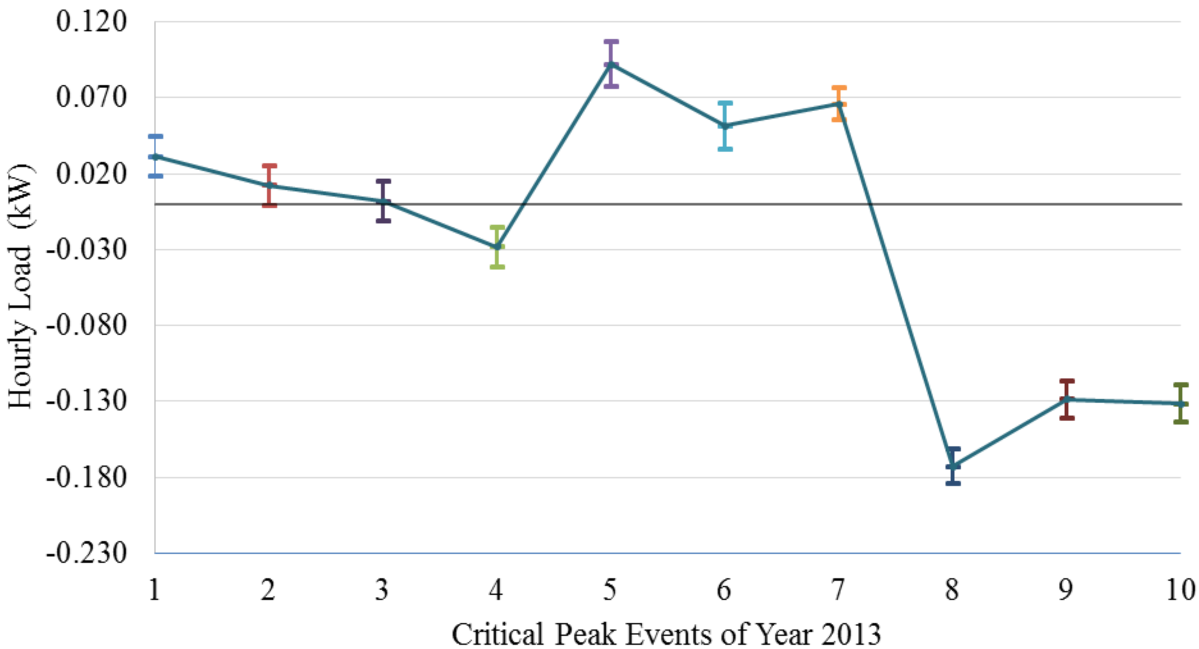
Similarly, coefficients of interaction variable of event-hour indicators with the hourly heat index show that the participants used more electricity during first and third critical peak events. Among different treatment groups, the regression results shows that CPP with IHD residents have statistically significant and consistent hourly load reduction across all four critical peak events of 2012.

Table 3-10: Event-to-Event persistent analysis of year 2012

	14-Sep	*21-Sep*	*25-Sep*	*5-Oct*
Event hours indicator	-2.288***	-0.777***	-2.362***	-0.916***
	(0.273)	(0.104)	(0.183)	(0.138)
Event hours indicator * heat index	0.030***	0.009***	0.036***	0.012***
	(0.004)	(0.002)	(0.003)	(0.002)
*Group*Hour*Event Indicators*Heat Indecx interaction terms*				
PTR	-0.001**	-0.001	-0.001	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
PTR with IHD	-0.001***	-0.001	0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)
CPP	-0.001	-0.001	-0.001	-0.001*
	(0.000)	(0.000)	(0.001)	(0.000)
CPP with IHD	-0.002***	-0.001**	-0.001**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations		14,904,158		
note: *** p<0.01, ** p<0.05, * p<0.1				

Figure 12 presents the mean difference of average electricity consumption between the treatment and control group customers during different 2013 critical event days. The estimates also contain the 95 percent confidence intervals. Please note that events 2 to 6 were called on consecutive days from July 15 to July 19 of 2013. The responses do not show any particular trend. We see that maximum reductions in second year occurred during the last three event periods. The average temperatures during these three events are very closely related and lie in the range of 80 F. Event 5 shows that treatment group customers used more electricity than control group customers. It might be due to the shift in electricity usage from earlier event day (event 4) to event 5[44]. Customers were unaware of critical peak event 5 during event 4 and may have shifted some of the electricity intensive work to the next day. And treatment customers may have completed the tasks on next day even though it was another critical peak event day.

Figure 3-13: Persistence Analysis – change in hourly electricity consumption (kW) – during critical peak events of 2013



We then compare residential customers' electricity consumption behavior between first and second years of critical peak events. The relevant results are the interaction of treatment group customers with year indicator at hours during the critical peak events. The regression results show that all treatment groups' consumption was lower in the second year's event hours than the first year's one. However, the response of CPP and CPP-IHD customers is statistically

[44] Events 4 and 5 occurred on July 17 and 18 of 2013.

significant. The electricity usage during event hours of second year of CPP customers is 0.219 kW lower than their usage in first years' event hours. Similarly, in the second year event hours, CPP-IHD customers consumed 0.278 KW lower than their consumption in the first year. Although we compare power usage during first and second year of the study, we note that a number of factors complicate the comparison, including the timing of the peak events in 2012 versus 2013 (the 2012 events were called in the fall, while the 2013 events were called during the summer); very warm weather conditions during the summer of 2013; and a shift in the rate treatment faced by some customers between 2012 and 2013.

Table 3-11: Persistence Analysis: year-to-year

Independent Variables	*Results*
Heat Index (F)	-0.003***
	(0.000)
Year indicator - *1 if year 2013; 0 if year 2012*	0.138***
	(0.012)
Year indicator * Before event Hours	0.141***
	(0.009)
Year indicator * Event hours	0.416***
	(0.032)
Year indicator * After event hours	0.351***
	(0.009)
Year indicator * During event hours * CPR Customers	-0.001
	(0.046)
Year indicator * During event hours * CPR-IHD Customers	-0.059
	(0.052)
Year indicator * During event hours * CPP Customers	-0.219***
	(0.043)
Year indicator * During event hours * CPP-IHD Customers	-0.278***
	(0.048)
Year indicator * During event hours * control-notification Customers	-0.063
	(0.043)
Number of observations	*26,427,323*

*note: *** p<0.01, ** p<0.05, * p<0.1*

Although the main objective of this study is to look at the peak load reductions due to various treatment rates, we also analyze if the event days had any impact on daily electricity consumption. In order to perform the analysis, we aggregated the hourly load data at the daily level. The difference-difference regression results with customer-level fixed effects show that treatment groups' daily electricity consumption during event days is lower than the control groups ones. The regression results are present in table 12. The daily electricity usage of CPR treatments – both without IHD and with IHD – is at least 1 kWh lower than the control group customers. For CPP group, even though the coefficients are negative, we fail to show statistical significance in daily electricity usage with the control group.

Table 3-12: Daily load analysis during event and non-event days

Independent Variables	*Year 1*	*Year 2*	*Both years*
Average Daily Heat Index (HI)	-0.121***	-0.109***	-0.113***
	(0.004)	(0.004)	(0.004)
Average Cooling degree hours	-0.862***	-3.546***	-1.581***
	(0.070)	(1.168)	(0.121)
Total Daily Cooling degree hours	0.003***	0.008***	0.004***
	(0.000)	(0.002)	(0.000)
Event Days	-1.725***	1.940***	0.746**
	(0.244)	(0.448)	(0.341)
Event Days * CPR	-0.279	-0.409	-0.944**
	(0.302)	(0.683)	(0.458)
Event Days * CPR-IHD	-0.065	-0.788	-1.006*
	(0.325)	(0.792)	(0.531)
Event Days * CPP	0.042	-0.836	-0.653
	(0.325)	(0.614)	(0.463)
Event Days * CPP-IHD	-0.513	-1.208*	-0.792
	(0.404)	(0.706)	(0.533)
Event Days * notification	-0.092	-1.323**	-1.212***
	(0.332)	(0.647)	(0.463)
Number of observations	*649,311*	*527,550*	*1,176,861*
Adjusted R2	*0.054*	*0.071*	*0.058*

*note: *** p<0.01, ** p<0.05, * p<0.1*

7.3 Hourly Load Analysis of Transitioning Group

The study also conducted a separate analysis for transitioning treatment group of customers on hours surrounding critical peak events. A group of participants were transferred from CPR (first year) to CPP (second year) treatment rates. This is an example of ‘carrot-stick’ approach – customers are in voluntary rebate program during the first, but are placed into ‘mandatory’ pricing structure in the second year. We noticed a large number of customers dropping out of the pilot study during the second year.

Table 3-13 presents regression results of transitioning group customers analyzing their hourly electricity consumption. Transitioning customers responded more actively to CPP than CPR treatment by reducing usage during event hours and by shifting their electricity load to hours surrounding critical peak events. The same IHD customers when placed in CPP rate reduced hourly electricity consumption by 0.11 kWh than when they faced CPR treatment. The results also show that transitioned treatment groups used more electricity before- and after critical peak event hours of second year as compared with the first year. The result of increase in usage before and after event hours and reduction in consumption during event hours indicate a higher impact of price treatment than rebate treatment.

Table 3-13: Hourly load analysis of transitioning treatment groups

Independent Variables	*Regression coefficients*
Heat Index	-0.003***
	(0.000)
Cooling degrees	0.032***
	(0.001)
Cumulative Cooling degrees	-0.000**
	(0.000)
Year 2 Indicator: Year 2 = 1; Year 1 = 0	-0.017**
	(0.007)
Year 2 Indicator * CPR-CPP	-0.012
	(0.011)
Year 2 Indicator * CPR-CPP-IHD	0.001
	(0.014)
Before Event Hours* Year 2 Indicator * CPR-CPP	0.197***
	(0.026)
Before Event Hours* Year 2 Indicator * CPR-CPP-IHD	0.114***
	(0.032)
During Event Hours* Year 2 Indicator * CPR-CPP	-0.008
	(0.034)
During Event Hours* Year 2 Indicator * CPR-CPP-IHD	-0.110***
	(0.042)
After Event Hours* Year 2 Indicator * CPR-CPP	0.177***
	(0.028)
After Event Hours* Year 2 Indicator * CPR-CPP-IHD	0.149***
	(0.037)
Number of observations	*9,747,996*
Fixed Effects	*Yes*
*note: *** p<0.01, ** p<0.05, * p<0.1*	

7.4 Energy Consumption Analysis

We also assess the impact of IHD technology on customers' electricity consumption. The regression results are presented in table 9 separately for 2012 and 2013. The regressions use month-fixed effects in order to control for the heterogeneity in electricity consumption that may arise due to weather affects. The first column presents the regression results for 2012, whereas the second column consists of 2013 results. As a robustness check, we also looked at the effect of IHD on daily electricity consumption and the regression results are very similar. The results of daily electricity usage are presented in the appendix.

The results show that the impact of feedback technology in monthly electricity consumption is considerable and statistically significant. On average, during the first year, customers with IHD technology decreased monthly electricity usage by 34.6 kWh as compared with the average monthly usage of customers without the continuous feedback system. However, the impact of IHD equipment in 2013 is considerably lower than seen in 2012 – the monthly electricity usage customers with the feedback technology is 12.7 kWh lower than the customers that do not possess the equipment. The higher impact seen in for 2012 may have to do with timing of installation of IHD technology. GMP distributed the IHD system during August 2012 right after the hot summer days. The model puts IHD customers in non-IHD group from March 2012 to July 2012 limiting the analysis for estimate the impact of technology during relatively milder weather.

We think the results of 2013 gives better estimates of the impact of IHD in monthly electricity usage. It is mainly for two reasons – the data is available for year around, and customers have IHD for at least few months and their behavior may be consistent. The log-linear model shows that this decrease in monthly load usage amounts to 2.0 – 5.3 percent reduction as compared with the non-IHD customers. The relevant study by Houde et al. shows the continuous feedback technology reduces electricity usage by 5.7%.

Table 3-14: Impact of IHD technology in monthly electricity usage (kW)

Independent Variables	*Year 1 (2012)*	*Year 2 (2013)*
Average Cooling degree hours	-37.402**	45.924**
	(17.591)	(19.250)
Average heat index	9.558***	5.086
	(2.714)	(3.558)
Customers with IHD	-34.616***	-12.707**
	(9.240)	(6.264)
Number of observations	*22,313*	*19,490*
Adjusted R2	*0.072*	*0.218*
Month-fixed effects	*Yes*	*Yes*
*note: *** p<0.01, ** p<0.05, * p<0.1*		

8. **Conclusion**

We study Green Mountain Power's customers' electricity consumption patterns in a response to the critical peak events during two-year long pilot study. Critical peak events are called when utility company anticipates very high demand during summer. Participants are notified by 6 pm of prior day before each critical event day. In total, GMP called four events during the first year and another ten events in the second year. According to the participants' treatment rates, customers either receive payment for lowering electricity usage below their baseline or have an opportunity to reduce their electricity bill by decreasing usage in order to avoid high pre-determined critical peak pricing. Moreover, we also analyze the change in total electricity consumption due to the installation of continuous feedback technology.

The analysis of customer-level electricity consumption shows that incentive based demand response programs has statistically significant impact in reducing peak load. Regardless of weather, both the CPR and CPP rate groups measurably reduced electricity usage, in the range of 6.0 – 10.3 percent, during the declared critical peak event. The CPR rate reduces peak load usage by 6.0 – 7.7 percent whereas the impact of CPP treatment rate is larger. The decrease in electricity consumption by CPP rate participants is between 6.8 and 10.3 percent during the critical peak events. The results also suggest that participants with IHDs show larger responses during non-event hours than customers facing similar electricity rates but are not equipped with the IHDs.

The results indicate that customers on CPR reduced their average hourly loads by 0.038 to 0.081 kW (6.0 – 7.7 percent), relative to a control group that was not notified of peak events and was not placed on any special rate during the critical peak event hours. Besides RCT analysis, we also conduct RED and LATE analysis for CPP related customers in order to account for the participants that opted-out of the pilot study. Customers on CPP exhibited larger average hourly load reductions of 0.045 to 0.142 kW (6.8 to 10.3 percent), relative to the control group.

Customers equipped with In-Home Displays (IHDs) generally exhibited larger reductions during peak events. While CPR customers equipped with IHDs exhibited reductions around 20% larger than CPR customers without the IHD, CPP customers equipped with the IHD exhibited critical peak reductions nearly twice as large, on average, as CPP customers without the IHD. Moreover, we also study the impact of IHD technology in monthly electricity usage. On average, IHD equipped participants' monthly energy consumption is 2.0 to 5.3 percent lower than the monthly energy usage of non-IHD customers.

Participants' electricity usage patterns differ across different critical peak event periods. We observed that customer responses were quite persistent during the hours of the critical peak event, indicating that customers take response actions at the beginning of critical peak times or prior to the start of the critical peak period, rather than managing their electricity usage on an hour-to-hour basis during critical peak events. Persistence of customer responses across critical peak events was less consistent.

None of the rate and IHD treatments induced a persistent response across multiple critical events. Therefore, the use of rate structures and information feedback alone provide insufficient motivation for consumers to reduce demand in any consistent way across multiple event periods. Based on our evaluation of GMP's DR programs during 2012 and 2013, neither critical peak pricing nor rebates are themselves sufficient to substitute for new capacity to meet resource adequacy requirements.

We acknowledge that our study lacks a way to measure the long-term energy efficiency adjustments that customers may make due to the impact of critical peak events and IHD technology. Even though we are able to analyze consumers' behavior due to various treatment rates, our study undermines the impact of long-run emergency DR programs. The impact of DR programs increases with the length of the program. Since the short-term electricity demand is more inelastic than long-term demand, customers' peak load reduction in the short-term may not be as significant as in the long run. King and Chatterjee (2003) find that the median price elasticity of electricity demand in short-run and long-run to be -0.2 and -0.90 respectively. A long term DR program may encourage customers to reduce electricity usage by purchasing energy efficient appliances and we might be able to see large peak load reductions.

9. **References**

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10. Appendix

Table 3-15: Impact of IHD technology in daily electricity usage

Independent Variables	*Load (kWh)*	*Load (kWh)*	*Log Load (log(kWh))*	*Log Load (log(kWh))*
Total daily cooling degree hours	0.175***	0.218***	0.018***	0.018***
	(0.048)	(0.040)	(0.003)	(0.003)
Average daily heat index	-0.732***	-0.789***	-0.068***	-0.070***
	(0.040)	(0.025)	(0.002)	(0.002)
Customers with IHD	-1.079***	-0.504**	-0.034***	-0.027**
	(0.056)	(0.218)	(0.003)	(0.011)
Constant	35.922***	16.365***	3.300***	2.514***
	(13.583)	(0.627)	(0.748)	(0.039)
Number of observations	*649,311*	*649,311*	*645,971*	*645,971*
Adjusted R^2	*0.035*	*0.090*	*0.026*	*0.089*
Customer-fixed effects	*No*	*Yes*	*No*	*Yes*
Day-of-the-year fixed effects	*No*	*Yes*	*No*	*Yes*

*note: *** p<0.01, ** p<0.05, * p<0.1*

Table 3-16: Analysis for hours with Heat Index greater than 80 F -Year 2

Independent Variables	*Results*
Heat Index (F)	0.004*
	(0.002)
Cooling degree days	0.018***
	(0.002)
Before Event hours	0.214***
	(0.008)
During Event hours	0.130***
	(0.009)
After Event hours	0.288***
	(0.009)
No of Observations	*631,580*

*note: *** p<0.01, ** p<0.05, * p<0.1*

Figure 3-14: Daily load profile during Event days of 2012 for IHD groups

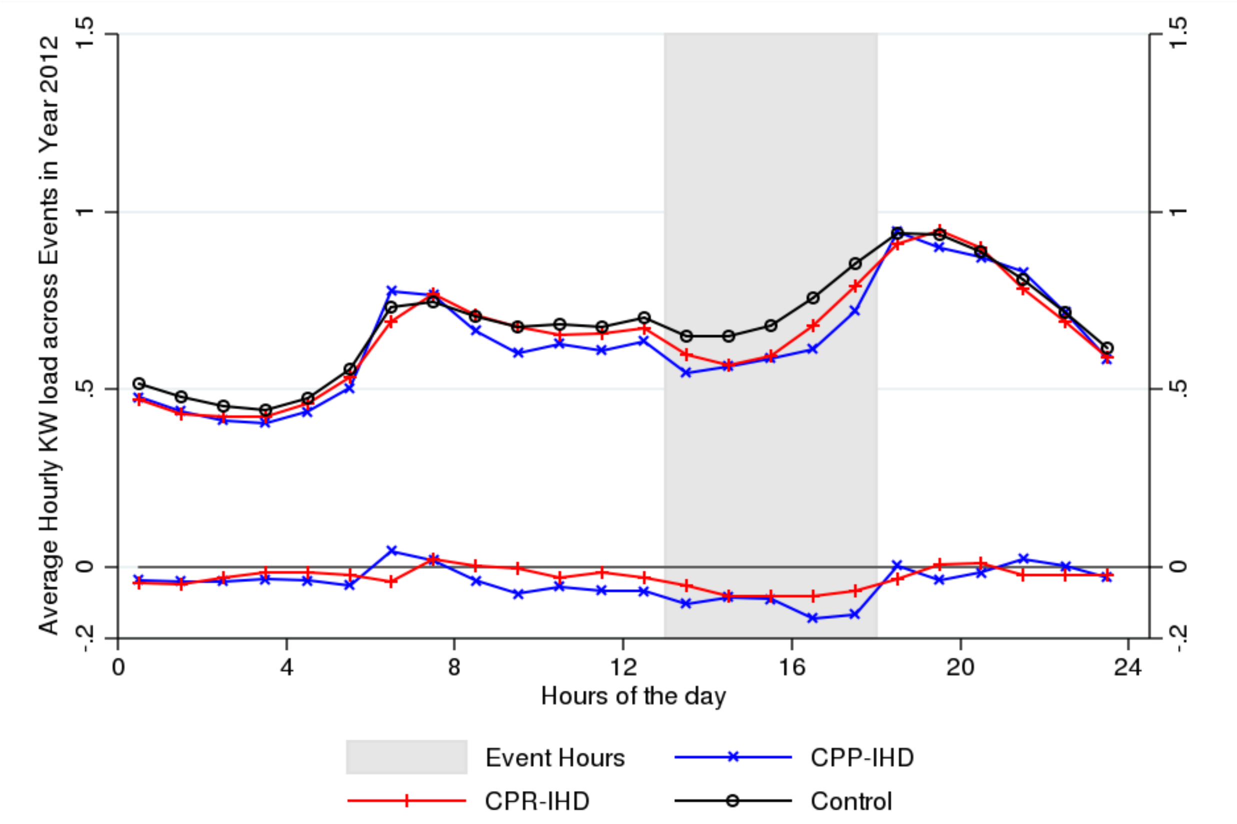


Figure 3-15: Daily load profile during Event days of 2012 for non-IHD groups

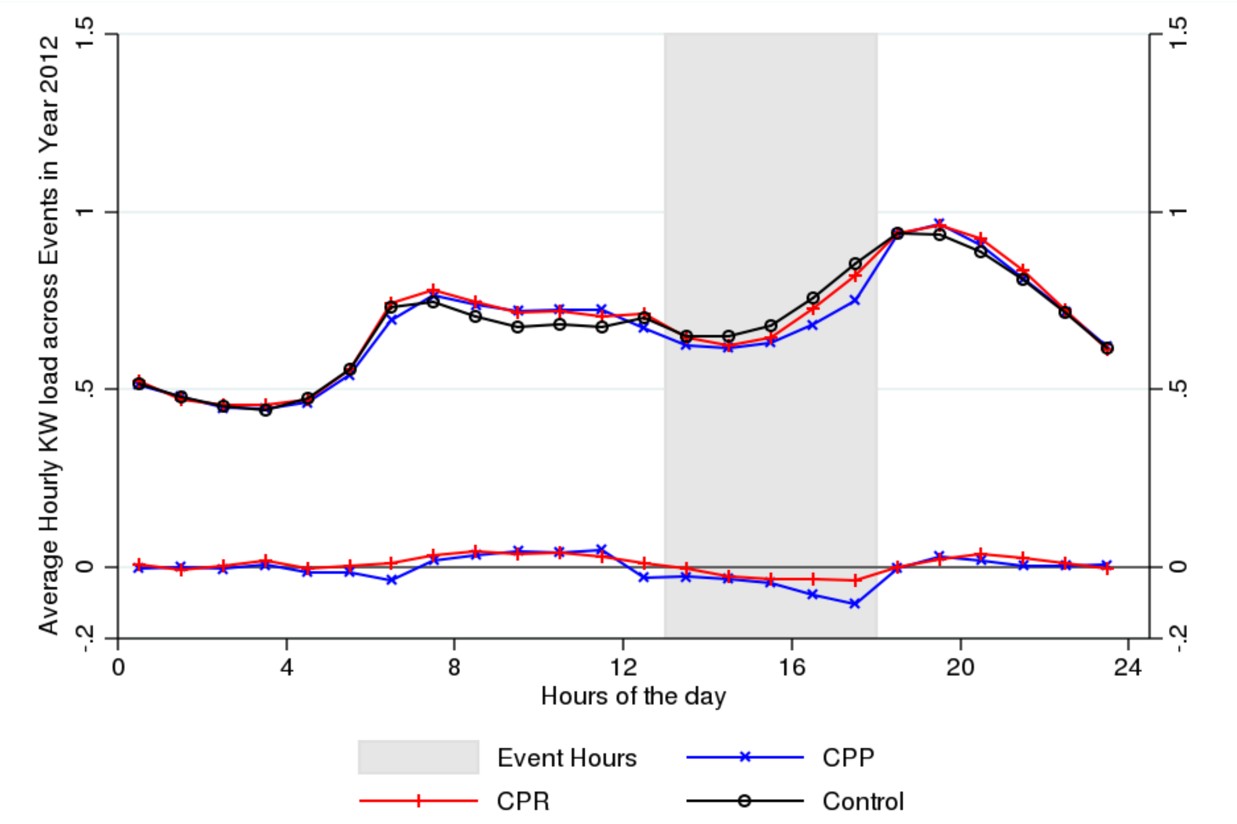


Figure 3-16: Daily load profile during Event days of 2013 for IHD groups

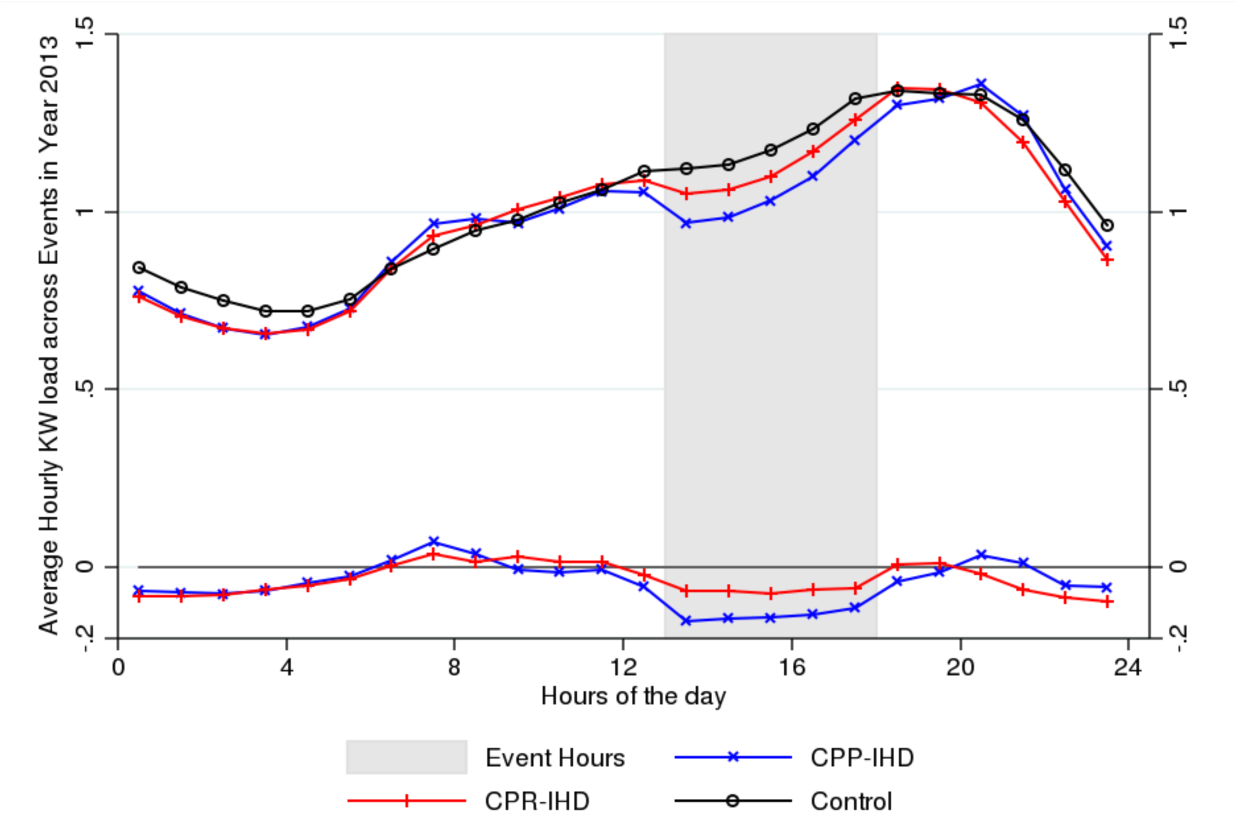
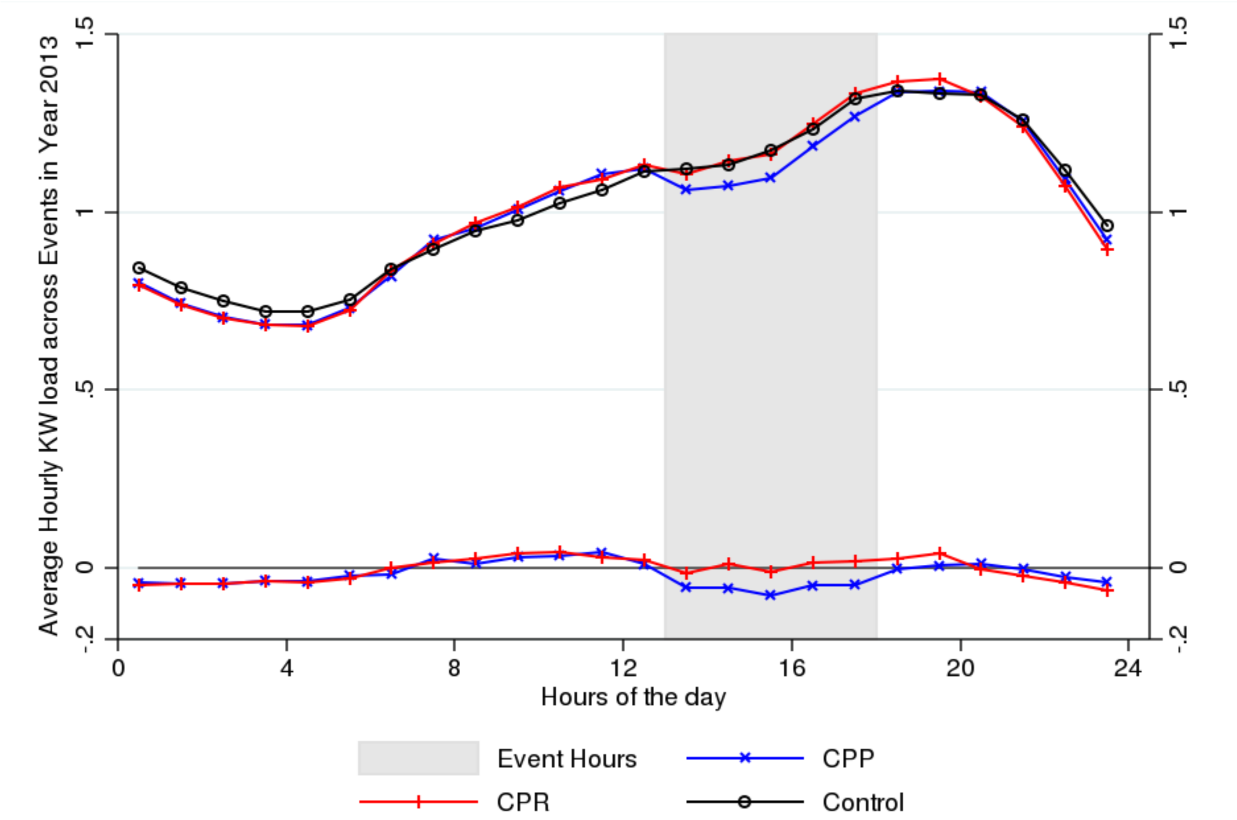


Figure 3-17: Daily load profile during Event days of 2013 for non-IHD groups



Chapter 4: Analysis of Load and Price patterns in the U.S. Electricity Sector

Abstract

This paper analyzes hourly electricity loads and marginal costs of electric entities with of extreme value theory (EVT), a concept widely used in the financial sector. For each year's hourly data of balancing authorities and utilities, we fit generalized extreme value (GEV) distribution and estimate the parameters of the distribution with an aim of comparing how these parameters have changed over time and market regions. We also account for the time dependencies, seasonalities, and near-time clustering present in the electricity markets – both for electricity load and prices – with the help of autoregressive conditional hetereskedastic models. that the results show that the distributions of hourly load and lambda values are fat tailed. Hourly lambda values have more extreme values generating fatter tails than hourly electricity load. We also show that extreme tail quantiles estimated with the GEV parameters at different percentile levels are comparable with the percentiles of actual observations.

Keywords: Extreme Value Theory, Generalized Pareto Distributions, AR/GARCH, electricity markets

1. **Introduction**

The United States electricity sector has undergone massive changes over the last few years. The deregulation of the industry has changed the way electricity is being traded and returns received by utilities. The emphasis on clean energy policy and climate change has increased grid-connected renewable generation, which in turn raises intermittency issues. Limited storability of electricity makes meeting dynamic electricity demand, especially during peak demand period, challenging and economically inefficient.

For a reliable and stable electricity system, utilities should be capable of meeting both total electricity demand and peak demand at all times. Since the safety and reliability of electricity systems are both compromised if there is a sudden change in electricity markets, there is a need to analyze how electricity transaction and load patterns, especially during high demand periods, have changed within and across different electricity markets. The study analyzes the periods of peak electricity demands and very high electricity prices using extreme value theory (EVT). For each year's hourly data of balancing authorities and utilities, we fit generalized extreme value (GEV) distribution and estimate the parameters of the distribution with an aim of comparing how these parameters have changed over time and market regions.

The electricity usage pattern is changing; the average peak demand growth is outpacing total electricity demand growth (citation needed). Spees (2008) points out that the fraction of capacity serving just peak load has increased during 1980 – 2006 period. Using hourly load data of New England Independent System Operator (NE-ISO) regions, Spees shows that 15% of the total capacity of ISO-NE ran only 0.9% of the time or less for the year of 2006[45]. The recent

[45] This calculation doesn't even account 8% reserve margin.

trend of increasing gap between the peak demand and average electricity demand raises few concerns. Only peak load serving capacity increase results in economic inefficiency since these infrastructures run only a few hours per year. New investments in both electricity generation and transmission sectors are capital-intensive. Analysis of peak electricity consumption pattern is important for planning and investment purpose since the load growth is the main reason for utilities to acquire additional generation sources (Berry, 2008).

Extreme value theory is a well-studied subject, however its use in the electricity sector is limited. Fuller (1914) and Griffith (1920) conducted the earliest work on the methods of application of EVT. Fisher and Tippet (1928) made a major development by concluding that extreme limit distribution can be only of three types. Gnedenko (1943) presented rigorous foundation for EVT and Gumbel (1958) proposed applications of EVT, which was previously treated theoretically. Few of the recent books such as Kotz and Nadarajah (2000) and Coles (2001) provide excellent theory and review of extreme value distributions.

In the electricity sector, most of the literatures on extreme value theory focus on modeling and estimating wholesale electricity prices of a single market region. Bosco et al (2007), Huisman and Kilic (2011), Bystrom (2005) and Chan and Gray (2006) use generalized extreme value distribution to AR-GARCH filtered price change series to investigate the tails of the electricity price change distribution. Spees (2008) treats peak load as extreme value to predict the total capacity necessary to serve forecasted load in the NE-ISO region. Spees (2008) then calculates the total capacity required to ensure meeting peak demand of NE-ISO with the help of EVT theory projected distribution around peak load. Our paper serves a different purpose. The paper provides a comprehensive analysis of extreme tail characteristics of different market regions' hourly electricity load and prices.

We use EVT to analyze hourly electricity load of the US electricity providers. First, the paper fits the GEV distribution to predict the parameters and analyze how these parameters change over time and geographic locations. This allows comparing the usage of generation capacity within one electric jurisdiction over the years and also between different electric entities and balancing authorities. Besides estimating the parameters of the most appropriate distribution, we can also predict the return value, that is the maximum value that the electricity price or load can reach in future. This helps us determine or forecast massive changes in future electricity demand. We also address time dependencies of hourly electricity load with the help of autoregressive conditional heteroskedastic models.

We also estimate extreme value parameters of hourly system lambda values of various balancing authorities. System lambda represents the marginal cost of the generating plant that meets the last MWh of electricity demanded. Wholesale electricity price comprises of system lambda and transmission congestion cost. We use hourly system lambda as a proxy for electricity prices. Similarly, balancing authority is the responsible entity within a metered area for reliable planning and operation of bulk power system. Its prime function is to continually balance the control area's scheduled and actual electricity interchange by dispatching generation units used for regulation.

The results demonstrate that the distributions of hourly load and lambda values are fat tailed. Hourly lambda values have more extreme values generating fatter tails than hourly electricity load. This is understandable because hourly load has upper limit due to physical constraints such as transmission lines and generation capacity. We also estimate extreme tail quantiles with the help of generalized extreme value parameters. The results show that extreme tail quantiles estimated with the GEV parameters at different percentile levels are comparable with the percentiles of actual observations

However, there are few caveats in our study in terms of data availability and use of common method across geographic regions. The data availability dictates the inclusion of electricity providers and balancing authorities in our analysis. The main source of data is the Federal Energy Regulatory Commission (FERC) 714 form. The hourly load and electricity data are not available continuously for all years. In order to analyze extreme occurrences of hourly electricity load, we are able to include 52 electricity providers for 2000 – 2012 and 118 electricity providers for 2006 – 2012 period. Similarly, for analyzing extreme changes in hourly lambda values, we have 16 balancing authorities for 2000 – 2012 period and 48 for 2006 – 2012 period. Moreover, we use a single method to estimate extreme value and autoregressive conditional heteroskedastic parameters for all electricity entities available in our study even though electric entities differ in many ways – size, type, market regulation, state policies.

The rest of the paper follows with the overview of the US electricity sector in section 2. We include brief background of extreme value theory and its implications in the electricity sector in section 3. Similarly, section 4 describes hourly electricity data and conducts tail analyses. In section 5, we compare generalized extreme value parameters across different market regions and years. We conclude in section 6.

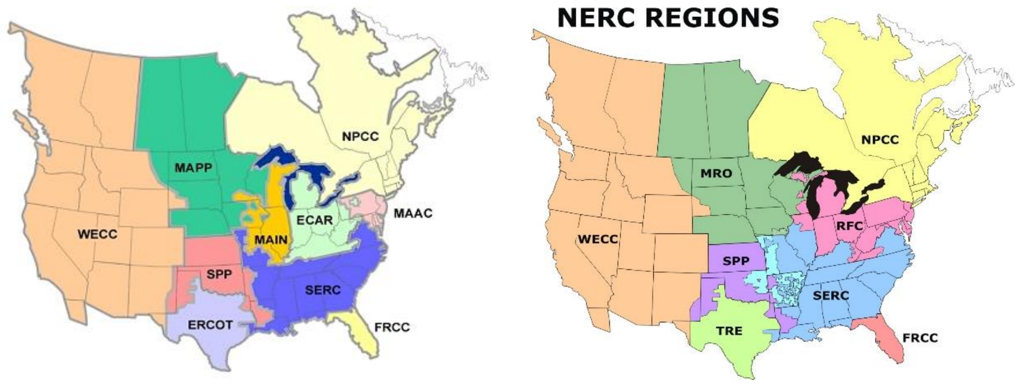
2. **Overview of United States Electricity Sector**

Electricity is significant part of the energy consumption that drives economy and environment. The total electricity generation of United States in 2012 is 4.047 TWh with average residential electricity price of 9.84 cents/kWh- ranging from 6.44 cents/kWh in Idaho to 15.89

cents/kWh New York, 16.35 cents/kWh in Connecticut (EIA, 2012a). There are various forms of electricity providers depending on the state, size, and regulations. In 2012, there were 3262 electricity providers comprising of 2006 publicly owned utilities, 193 investor-owned utilities (IOUs), 973 cooperatives, and 181 power marketers. Even though the number of IOUs is significantly smaller than publicly owned utilities, IOUs are responsible for 40 % of 4.167 TWh of generation and publicly owned utilities generate 10.4 %. Other significant portion of generation comes from the non-utility generators. (2013-14 Annual Directory and Statistical Report, American Public Power Association)

The federal regulatory bodies, Federal Energy Regulatory Commission (FERC) and North American Reliability Corporation (NERC), oversee reliability, sales, and transmission of electricity in United States. The Federal Energy Regulatory Commission (FERC) is an independent body that regulates the interstate transmission and wholesale sales of electricity. The Energy Policy Act of 2005 gave more responsibilities to FERC in the areas of smart grid, demand response, and integration of renewables. The North American Reliability Corporation ensures the reliability of the bulk power system by developing and enforcing the Reliability Standards. NERC regions include all of US territory and some parts of southern Canada. In figure 1, we show NERC jurisdiction over US and Canada.

Figure 4-1: North American Electric Reliability regions (EIA, 2012b)



NERC Region prior 2005 NERC Region after 2005

The United States mainly consists of two types of electricity markets – regulated and deregulated. The regulated market has a vertically integrated model responsible for generation, transmission, and distribution systems. The regulated market can also have a separate entity responsible for the distribution section of the electricity market. The second electricity market type is based on competitive model in both wholesale and retail electricity sectors and covers 66 % of the total U.S. consumers (Neenan and Flaim, 2010).

In regulated market, which was predominant before restructuring, a single agent has the responsibility of electricity generation, transmission, and distribution for a certain rate of return on investment. However, consumers are responsible for securing commodity and transmission in the deregulated market. Similarly, in the competitive market, generators can sell their output through spot market, bilateral contracts, or directly to retail customers.

The key difference in these two markets is the way electricity prices are set. The price in the restructured market is 'forward-looking' reflecting the marginal costs and transmission congestions and does not consider sunk costs. Whereas, regulated prices are based on average and historic costs. However, there are some similarities between two markets – both operate in deregulated wholesale commodity and transmission markets and both have non-competitive distribution.

Electricity is a complex commodity – physics governs its flow and economics dictates the dispatch. The electricity sector, especially operating in the competitive market, bears price and demand risks that arises from the nature of the product itself. Generally the risks associated with the electricity markets can be divided into four categories – volume, regulatory, transaction, and market. Some of the risks generate from demand variations, use of multiple fuel sources, production constraints, regulation, reliability measures, and lack of grid-level storage and accurate weather predictions. Moreover, new energy policies such as renewable portfolio standards, production tax credits, demand response and energy efficiency programs, incentives promoting distributed generation also increase burden to maintain reliability standards. The increase in risks, driven by market, regulations, and politics, makes providing reliable and continuous supply of electricity a challenging job.

Managing risks and also maintaining reliability and safety standards at the same time is a challenging task. This study provides a different approach to predict future spikes by analyzing historic electricity demand and lambda data. This study helps electricity providers to prepare for extreme situations.

3. Extreme Value Theory and Implication in the Electricity Sector

The hourly electricity demand varies periodically – daily, weekly, and seasonally. In daily basis, electricity demand is high during daytime. The electricity usage is high during summer season, mainly demand driven by the use of air conditioner and long daylight. The periodic variations in the electricity load generate extreme values. Figure 2 gives hourly load of PJM region during period of 2000 – 2012 in a time-series plot. We can see that the hourly load values are extremes in few instances throughout the year.

Similarly, the nature of electricity leads to non-constant and high electricity marginal costs. Some of the main properties are non-storability, *inflexibility in changing generation amount*, and limitations in transferring bulk amount of electricity. Figure 3 contains the time-series plot of hourly lambda values of New York ISO (NYISO) region. The figure shows that the extreme positive lambda values are very high compared to the median lambda values. Moreover, the high sample kurtosis values of hourly electricity load and lambda values suggest that the distributions have fat tails.

Figure 4-2: Hourly load (GW) plot of PJM region from 2000 to 2012

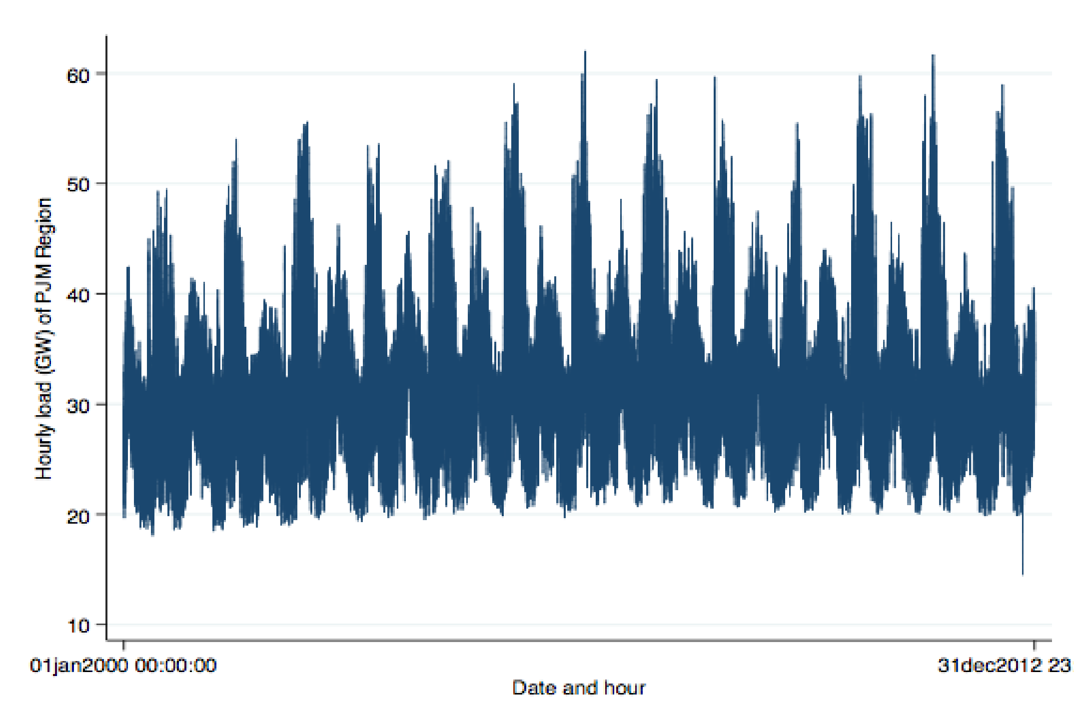
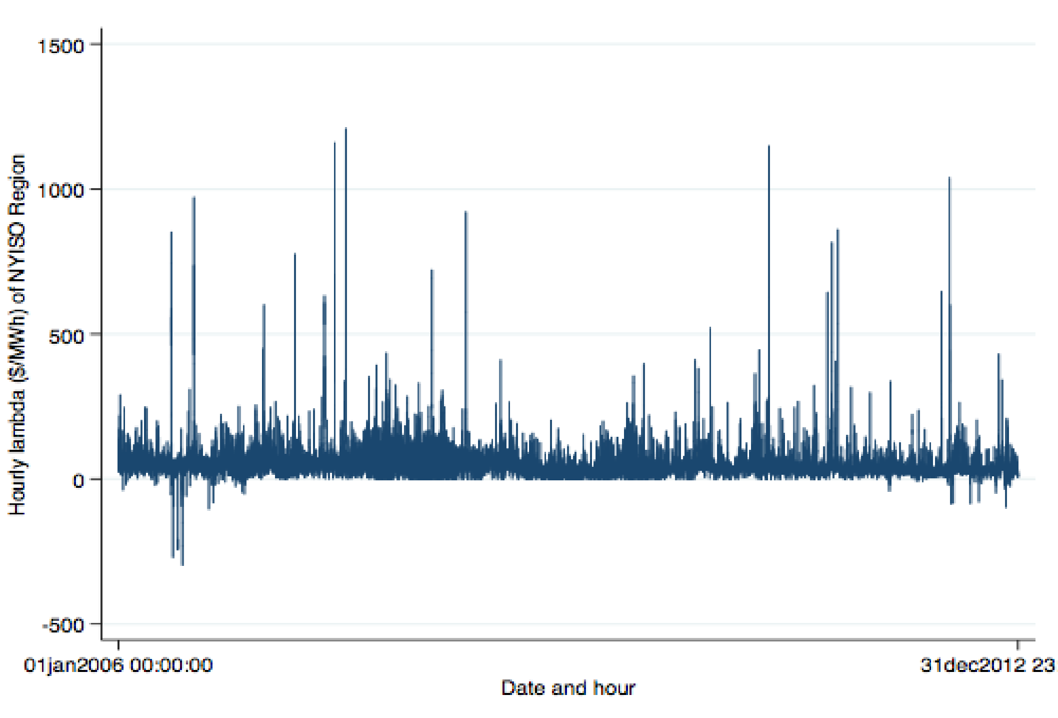


Figure 4-3: Hourly lambda ($/MWh) of New York ISO from 2006 to 2012



There are at least three ways to estimate Value-At-Risk (VAR). They are variance-covariance method, historic simulations, and EVT. The extreme value fits extreme quantiles better than conventional approaches and thus is better method for observations with fat tails (Embrechts, 2000).

Extreme value theory (EVT) allows us to model extreme and rare events of independent, identically distributed random variables. It is widely used in finance, hydrology, and meteorology sectors. Unlike classical statistics that focus analysis on average behavior of stochastic processes, EVT focus on the tail of the distributions and quantify the stochastic behavior of events that are unusually large or small. We use EVT to fit the peak hourly electricity demand (and lambda values) over the years and estimate the parameters of the distribution. However, analyzing the electricity markets with the help of EVT is more complex than the financial market or meteorology due to the distinctive features arising from non-storability and highly correlated observations both in daily and seasonal basis.

We can use classic extreme value theory in at least two methods - block maximum and peak over threshold (POT). In block maximum method, data are grouped into consecutive sequences generating a series of maximas within those groups to which GEV distribution is fitted; whereas in POT methods, we fit GEV distribution to those observations that cross over certain high threshold value. In the following paragraph, we discuss both methods. However, we choose to use peak-over-threshold method to estimate extreme value parameters since it utilizes more extreme observations than block maximum method.

3.1 Block Maximum Method

The theory of block maximum method discussed here is heavily drawn from textbooks of Coles (2001) and Kotz and Nadarajah (2001). For a large value of *n*, independently identically distributed observations $X_1, X_2, \ldots$ are grouped into sequence of observations of length *n* such that $M_n = \max\{X_1, \ldots, X_n\}$ and M_n follows a GEV distribution.

The cumulative distribution function of generalized extreme value (GEV) is:

(1) $$F(x;\ \mu, \sigma, \xi) = \exp\left[-\left(1 + \frac{\xi(x-\mu)}{\sigma}\right)\right]^{-\frac{1}{\xi}}$$

where $\mu \in R$ is location parameter; $\sigma > 0$ denotes scale parameter; and $\xi \in R$ is shape parameter. The μ and σ are analogous to the mean and standard deviation of the normal distribution. The shape parameter, ξ governs the tail behavior of the distribution. GEV distribution can be one of its three types based on the shape parameter.

With the help of hourly data, the GEV distribution helps us determine the type of the distribution based on the tail behavior rather than choosing the type of distribution before fitting the observations. Using a GEV distribution of equation (1) rather than three different EVT distributions separately simplifies the statistical implementation. The uncertainty of predicted ξ tells us the level of certainty related with the type of distribution suggested by the data (Coles, 2001). Generalized extreme value distribution can take one of the three forms discussed below based on the numeric value of ξ .

For $\xi \rightarrow 0$ and $-\infty < x < \infty$, we have type I (Gumble) distribution which has a tail structure similar to the normal distribution. The Gumble distribution simplifies to

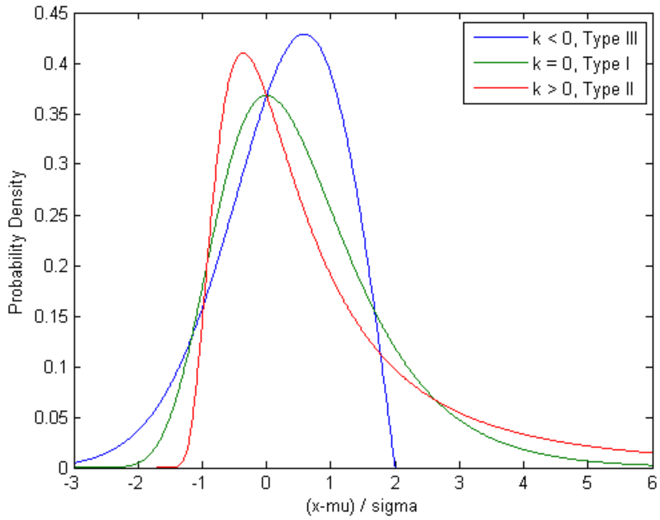
$$(2) \quad F(x;\ \mu, \sigma, \xi) = \exp\left[-\exp\left(-\frac{(x-\mu)}{\sigma}\right)\right]$$

For $\xi > 0$ and $\mu - \frac{\sigma}{\xi} < x < \infty$, we have type II (Frechet) distribution with a fat tail.

Similarly, for $\xi < 0$ and $-\infty < x < \mu - \frac{\sigma}{\xi}$, we have type III (Weibull) distribution with a finite positive tail. The figure 1 displays all three types of GEV distributions (Mathworks example)[46]. Please note that ξ is denoted by k in the figure below.

[46] http://www.mathworks.com/help/stats/examples/modelling-data-with-the-generalized-extreme-value-distribution.html . Accessed November 18, 2013.

Figure 4-4: Types of extreme value distributions



The parameters of the GEV distribution – μ, σ, ξ – are estimated by fitting the GEV distribution to the observed hourly electricity data with the help of maximum likelihood estimation.

The log-likelihood function for GEV distribution

(3) $l\ (x;\ \mu, \sigma, \xi) = max_{(\ \mu,\sigma,\xi)} \ln(f(x;\ \mu, \sigma, \xi)$

where f is a probability density function of equation (1) such that

(4) $f(x;\ \mu, \sigma, \xi) = \ \exp\left[-\left(1 + \frac{\xi(x-\mu)}{\sigma}\right)\right]^{-\frac{1}{\xi}} \frac{1}{\sigma} \left\{1 + \frac{\xi(x-\mu)}{\sigma}\right\}^{-\frac{1}{\xi}-1}$

for $1 + \frac{\xi(x-\mu)}{\sigma} > 0$ and $\xi \neq 0$

(5) $f(x;\ \mu, \sigma, \xi) = -\exp\left(-\frac{(x-\mu)}{\sigma}\right) - \frac{(x-\mu)}{\sigma}$ for $\xi = 0$

See Coles (2001) (page 56) for limitations on maximization of equation (4) and (5).

3.2 Peaks-Over-Threshold Method

The other method of fitting extreme value distribution is through peak-over-threshold (POT) where observations that are larger than certain threshold level are taken despite the blocks they belong to. Peak-over-threshold method uses data more efficiently than the block-maximum method since it allows us to use more extreme observations. Block maximum takes only a single maximum value from a sequence. Multiple extreme events might occur within a period of time, thus using POT allows us to choose all the rare events as long as they are larger than the threshold value.

However, choice of threshold level has a tradeoff between variance and bias – a high threshold level would leave few observations for GEV fitting generating large variance, whereas low threshold level may result in bias parameter estimates due to large number of exceedances and may violate asymptotic assumption (Coles, 2001; McNeil and Frey, 2000). Thus, the choice of threshold level or number of exceedances is very important implementation in extreme value theory. For peak over threshold (POT) method, we keep threshold level at 95 percentile of all observations available within a year. This gives us 438 observations for a non-leap year to estimate extreme value parameters with the help of maximum likelihood method. Keeping threshold level fixed at 95th percentile also addresses the non-stationary property of the dataset by adjusting the threshold level accordingly. As the average of load (and lambda prices) changes with time, picking the threshold level at 95 percentile will adjust with the properties of observations within that year.

For $X_1, X_2, \ldots$ i.i.d. observations, the description of stochastic behavior of extreme events, exceedances over large threshold u, is given by the conditional probability

(6) $\Pr(X > u + y \mid X > u) = \frac{1-F(u+y)}{1-F(u)}$, $y > 0$

where y is observations over the threshold level u.

Following McNeil and Frey (2000) and Bystrom (2005), excess distribution of data series X above threshold level u can also be represented by

(7) $F_u(y) = P(X - u \le y \mid X > u) = \frac{F(u+y)-F(u)}{1-F(u)}$, $0 \le y < x_R - u$

where is the x_R right endpoint of F.

The observations greater than the threshold level are asymptotically distributed and follow a Generalized Pareto Distribution (GPD) (Gnedekno, 1943).

(8) $H(y|X_i > u) = 1 - \left(1 + \xi \frac{y}{\sigma_u}\right)^{-\frac{1}{\xi}}$

such that $y > 0$ and $\left(1 + \xi \frac{y}{\sigma_u}\right) > 0$ where $\sigma_u = \sigma + \xi(u - \mu)$

As in GEV, the shape parameter ξ determines the behavior of the family of distributions defined by Eq. (7). Generalized Pareto Distribution also has three types of distribution based on the shape parameter ξ .

Gumbel distribution when $\xi = 0$ such that

(9) $H(y) = 1 - \exp\left(-\frac{y}{\sigma_u}\right)$

Pareto (Frechet) distribution when $\xi > 0$ such that

(10) $1 - H(y) \sim c\, y^{-\frac{1}{\xi}}$

Similarly, for $\xi < 0$, the GPD becomes a weibull distribution with the upper end point,

(11) $w_f = \frac{\sigma_u}{|\xi|}$.

The log-likelihood function for GPD distribution

(12) $l\ (y; \sigma, \xi) = max_{(\sigma,\xi)} \ln(h(y; \sigma, \xi)$

where h is a probability density function of equation (7) such that

(13) $h(y; \sigma, \xi) = \frac{1}{\sigma}\left(1 + \frac{\xi}{\sigma} y\right)^{-\left(1+\frac{1}{\xi}\right)}$ for $\left(1 + \xi \frac{y}{\sigma}\right) > 0$ and $\xi \neq 0$

(14) $h(y; \sigma, \xi) = \frac{1}{\sigma}\exp(y)$ for $\xi = 0$

We determine both the shape parameter, ξ , and the scaling parameter, σ , by fitting the GPD to the actual data with the help of maximum likelihood method. We assume that the number of excess above threshold, n_u , are iid that follows exact GPD. Smith (1987) shows that, under this assumption, the parameter estimates, $\hat{\xi} = \hat{\xi}_{n_u}$ and $\hat{\sigma} = \hat{\sigma}_{n_u}$, of GPD are consistent and asymptotically normal as $n \rightarrow \infty$, given $\xi > -1/2$.

Next, we estimate extreme quantiles with the help of extreme value parameters and threshold value. In order to derive extreme quantiles, we start with equation (7),

(15) $F(u + y) = F(u) + F_u\ (y)\ (1 - F(u))$

Empirically, we can write $F(u) = \frac{n-n_u}{n}$ and $1 - F(u) = \frac{n_u}{n}$ where n is the total number of observations and n_u is the number of observations above the threshold level. Similarly, substituting $F_u(y)$ by $H(y|X_i > u)$ from equation (8) and replacing $u + y$ with x , we get

(16) $F(x) = \left(\frac{n-n_u}{n}\right) + \left[1 - \left(1 + \xi \frac{y}{\sigma_u}\right)^{-\frac{1}{\xi}}\right] \frac{n_u}{n}$

(17) $F(x) = 1 - \frac{n_u}{n} \left(1 + \xi \frac{x-u}{\sigma_u}\right)^{-\frac{1}{\xi}}$

With the help of parameter estimates and equation 17, we estimate tail quantile of the distribution. Quantiles are the inverse of cumulative distribution function. The tail quantiles assess the risks that the electricity sector is exposed to and investigates some 'worst-case' scenarios. Analyzing quantile estimates is analogous to calculating value-at-risk in the finance and investment sectors. With the help of tail quantiles, utilities can estimate the percentage change in electricity load or prices in every certain period of time. Or conversely, they can estimate the probability that the electricity demand or prices are higher than certain values. The objective of this study is to calculate the quantile estimates by electric entities.

By inverting equation 17, we find the tail quantile estimates of the distribution (Bystrom, 2005)

$$\alpha_p = u + \frac{\sigma}{\xi}\left(\left(\frac{n}{n_u}p\right)^{-\xi} - 1\right) \tag{18}$$

The equation 18 gives the quantile estimation with the help of GPD estimators. We assume that the observations above threshold show i.i.d. characteristics. This may not be the case for the electricity load and prices as they exhibit non-stationary processes with characteristics that change systematically through time. The following subsection explains the process that we use to address time dependencies in the electricity sector.

3.3 Time Dependencies in Electricity Sector

The seasonal variations of electricity demand give arise to serially correlated and non-stationary electricity load and lambda values. There is a need to account for time dependencies, seasonalities and near-time clustering in the electricity markets – both for electricity load and prices – before employing EVT since EVT relies on i.i.d. random observations. It is unreasonable to use models that assume time-constant random variations in electricity demand. The hourly electricity load from a hot summer day differs considerably from a winter day. Non-stationary processes give arise to large variance of error terms. Moreover, high or low electricity demand periods occur together resulting in some degree of autocorrelation. Engle (1982) proposes to use autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models for the time-series analysis. The ARCH models seek to estimate time-dependent volatility as a function of observed prior volatility (Stata Crop, 2013). GARCH models do not only account for heteroskedasticity but also controls for volatility clustering of the electricity sector.

Autoregressive models are widely used in the financial in finance due to time-dependence returns. McNeil and Frey (2000) combine three approaches – GARCH modeling, pseudo-maximum-likelihood estimation, and extreme value theory to study the tail distribution of the financial data by addressing its heteroskedastic nature. The paper first uses AR-GARCH to filter the data by accounting the possible dependencies in the financial market and then applies extreme value techniques. The residuals after filtering are more likely to show *i.i.d.* characteristics than the raw data. Bystrom (2005) and Chan and Gray (2006) extend McNeil and Frey's method to analyze electricity prices of NORD pool that operates market in Norway, Sweden, and Denmark.

We use AR(1), AR(2), and AR(24) to consider hourly and daily profiles in order to take care of diurnal in the electricity demand. Similarly, GARCH(1,1) models conditional volatility as a function of past conditional volatilities and returns (Bystrom, 2005). In GARCH(1,1), the first number in the parentheses refers to the autoregressive lags, or ARCH terms, whereas the second number specifies the moving average lags or GARCH terms (Engle, 2001).

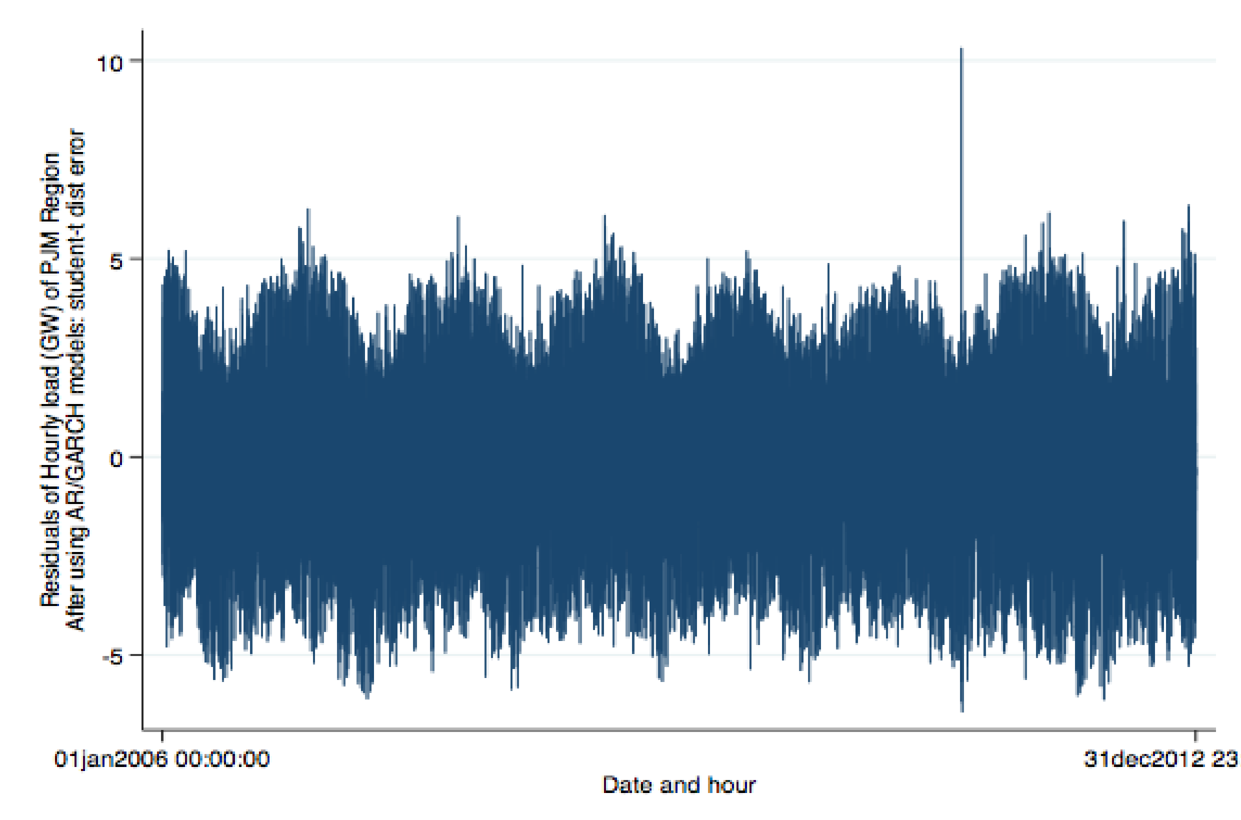
(19) $$x_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \beta_3 x_{t-24} + \varepsilon_t$$

(20) $$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 \sigma_{t-1}^2$$

where x_t is hourly electricity load or lambda values, ε_t^2 is the squared residuals (or innovations), σ_t^2 is the conditional variance of ε_t, $\widehat{x_t}$ is the conditional mean, γ_1 , γ_2 are the ARCH and GARCH parameters respectively. Using the difference of consecutive terms, $\mathrm{x_t} - \mathrm{x_{t-1}}$, instead of the observed value also helps get rid of time trend to some extent.

Engle (1982) assumed that error term, ε_t , follows a Gaussian distribution: $\varepsilon_t \sim N(0, \ \sigma_t^2)$. However, papers such as Bystrom (2005) and McNeil and Frey (2001) suggest that the extreme distributions are leptokurtic, meaning the observations are clustered resulting in narrower pick than the normal distribution. The assumption that the error structures follow *t*-distribution allows us to incorporate the leptokurtic nature of distribution. The *t*-distribution has fatter tails than the normal distribution. For our study, we assume error structures to be both Gaussian and *t* – distributions and estimate quantiles accordingly. Figure 5 is the time-series plot of residuals of PJM's hourly load after using AR/GARCH model. Comparing this figure with PJM's hourly load plot of figure 2, we can conclude that most of the variations arising from time dependencies and seasonalities are smoothen out.

Figure 4-5: Time-series plot of residuals of PJM hourly load after using AR(1), AR(2), AR(24), and GARCH(1,1) model during 2006 – 2012



Our objective of using autoregressive models is to improve on quantile estimated from GPD distribution. We acknowledge time dependencies in data by calculating conditional quantiles with the information estimated with the ARCH and GARCH models. Specifically, we use conditional mean – predicted value from equation (19) – and volatility of the conditional mean model to estimate conditional quantiles. The conditional tail quantile estimates,

(21) $$\alpha_{t,p} = \hat{x}_t + \sigma_t \, \alpha_p$$

where $\hat{x}_t$ and σ_t are the conditional mean and volatility from the AR-GARCH model.

α_p is the unconditional quantile estimated in equation (18).

4. **Data Description and Tail Analysis**

The data for the study comes from the Federal Electric Regulatory Commission (FERC) through its 714 form. The hourly load and lambda information of electric utility balancing authority and planning areas of United States are available from 1993 – 2012. The Federal Power Act requires each balancing authority area submit Parts I (Identification and Certification), II (Schedule 1: Generating plants included in reporting balancing authority areal; Schedule 2: Balancing authority area monthly capabilities at time of monthly peak demand; Schedule 3: Balancing authority area net energy for load and peak demand sources by month; Schedule 5: Balancing authority scheduled and actual interchange; Schedule 6: Balancing authority area system lambda data and description of economic dispatch), and IV of FERC 714 forms.

Whereas each electric utility with its planning area annual peak demand greater than 200 MW is required to submit Parts I, III (Schedule 1: Electric utilities that compose the planning area; Schedule 2: Planning area hourly demand and forecast summer and winter peak demand and annual net energy for load), and IV for FERC 714 forms (FERC, 2013)[47], the relevant datasets for our study are part II (schedule 6) and part III (schedule 2) of FERC 714 forms.

The datasets are available from three different sources within the FERC website. Hourly load and lambda of electric utility and balancing authority are grouped together according to their NERC regions for 1993 – 2004 period. The data for 2005 is available through Commission's eLibrary page. For 2006 – 2012 period, data are available in a single comma-separated value file. Importing and cleaning data from 2006-2012 is straightforward process. However, the process of data importing and cleaning for 1993 – 2004 was a laborious owing

[47] https://www.ferc.gov/docs-filing/forms/form-714/overview.asp Accessed: November 19, 2013

mainly due to the variations in the format of the data between regions and years. Data formats for few NERC regions are consistent across years, whereas for most of the regions, there is no particular format. The following paragraph describes the importing and cleaning process in detail for 1993 – 2004 period.

I wrote *STATA* program to automate the data importing and cleaning process for NERC regions – Western Electricity Coordinating Council, some balancing regions in Mid-Continent Area Power Pool – which have load and lambda prices available in consistent text (.txt) format over the years. The region that do not have consistent data format available, I employ a two-step procedure for importing. I first imported the raw data in excel, deleted information other than the load and prices and saved them in *csv* format. The saved *csv* data files are then imported in *STATA*. There are a few regions with no date-time stamped and only a single column of either load or lambda data available. The time and date information is not so important while estimating GPD parameters. However, for the AR-GARCH models, we first need to declare the data to be time-series and thus need time and date information. I assign the date and hour information to these data files if, and only if, the number of observations equals the total number of hours in that particular year.

The 2005 data is available through FERC's eLibrary. The identifier variable for 2005 data is the unique filename given by FERC during the time of uploading data by respective control areas or balancing authorities. Using these unique filenames and character names of the uploading agencies, I was able to assign the respondent ID – unique ID of electricity entities provided by FERC – manually. This way, we were able to get hourly load or lambda or both datasets for 85 different entities.

The identifier variable for pre-2005 FERC 714 data is unique EIA code, whereas FERC data from 2006 onwards have unique respondent ID. The separate excel file in post-2006 folder provides respondent ID with their corresponding EIA code. Leveraging this information, we connect pre- and post-2006 control areas. I merge this dataset with pre-2005 load and lambda data by unique EIA code. Similarly, I use the same dataset to merge with post-2006 dataset by respondent ID. This way, we were able to connect half of the pre-2005 load data, about 2.46 million observations, with the post-2006 dataset. The dataset, relating EIA code and respondent ID, does not contain information for the control areas for the other half of the pre-2005 data.

We exclude pre-2005 observations that have missing respondent ID – unique identifier of post-2006 dataset. In other words, we do not include pre-2005 data if the data are not available for the post-2006 period. There are various reasons for the discontinuity of hourly load and lambda data in post-2006 period. Some of which are changes in the NERC and FERC jurisdictions, electricity restructuring, and mergers and acquisitions.

In order to include the geographic information, I include the state of the Electricity providers and balancing authorities. I assign states to respective control area/ balancing authority based on their headquarter address. And with the help of states, we can also assign census regions and divisions for respective electric entities. We use this information to find the geographic distributions of the respondent IDs.

The final imported dataset consists of 9.72 million hourly load observations and 3.34 million hourly lambda values spanning the period from 1993 – 2012. The load data is of 119 unique electricity providers, whereas lambda data comprises of 48 unique balancing authorities.

Before analyzing the results, we find a list of electricity providers that have data available for continuous years of the time period we consider. By keeping the list of electricity-providers constant over the years, we can compare the results across different years and geographic regions. Since the source of hourly data varies, we were not able to get the data for all years of period 1994 – 2012. Moreover, the change in regulation and merging of electricity utilities and balancing authorities has also lead to discontinuity in the dataset. If we want to include only electric entities that have data available all years (from 1994 - 2012), we will have very few respondents. Similarly, if we have shorter period (from 2006 – 2012), then there will be less variation within the respondent ID. First, we consider three different time periods and find the list of respondents that have hourly observations consecutively available for periods of (i) 2006 – 2012, (ii) 2000 – 2012, and (iii) 1994 – 2012. Then, we decide the time-period to conduct further analysis.

Tables 1 and 2 give the number of unique electric entities that have results available for all years in each time period. Moreover, the table also includes number of unique electricity providers by Census Regions in different time period. For load data, there are only 9 (148)[48] unique electricity providers that have results available for all years from 1994 – 2012. Whereas there are 52 (402) providers for 2000 – 2012 period and 118 (837) electricity providers for 2006 – 2012 periods. The table 1 further separates the electricity providers by census region. In any of the three time periods considered, South region has maximum number of electricity providers with hourly observations available for all years. South region has larger number of electricity

[48] Numbers in the parentheses represent total number of observations (by respondent id and year) available in each group.

providers because of lack of ISO/RTOs in the area. The electricity providers in the South region serve small area as compared with the Northeast and West regions.

Table 2 provides the number of Balancing Authorities that have hourly lambda observations available for all years in each time period. There are only 7 (99) unique respondents – all in Midwest and South regions – that have results available from 1994 – 2012. Similarly, there are 16 (190) Balancing Authorities for 2000 – 2012 period and 48 (343) Balancing Authorities for 2006 – 2012 period. As the load data results, the South region has maximum number of Balancing Authority available in all four categories.

Table 4-1: Unique Electricity Providers by Census Regions for balanced panel of load results

Census Region	*from 1994*	*from 2000*	*from 2006*
Midwest	0	7	24
Northeast	2	3	8
South	4	15	50
West	3	27	36
Total	*9*	*52*	*118*

Table 4-2: Unique Balancing Authorities by Census Regions for balanced panel of lambda results

Census Regions	*from 1994*	*from 2000*	*from 2006*
Midwest	2	3	8
Northeast	0	1	5
South	5	12	23
West	0	0	12
Total	*7*	*16*	*48*

For hourly load analysis, we choose 2000 – 2012 since it has 54 unique respondents in this group giving us sizable observations and variations. Table 3 provides detailed descriptive statistics of hourly load (GW) of electricity providers that are available from 2000 to 2012. Among 54 unique respondents, average hourly electricity demand is 3.53 GW. The average hourly load of electricity providers varies from 0.13 GWh of City of Burbank, CA (*respondent id 195*) to 32.01 GWh of PJM Interconnection (*respondent id 230*). Majority of the electricity providers, 46 out of 54, have average hourly load of less than 5 GW.

Kurtosis is a measure of whether observations are peaked or flat relative to a normal distribution. In STATA, the kurtosis value of a perfectly normal distribution is 3. In the data sample, 41 out of 54 electricity providers have kurtosis value greater than 3. The sample kurtosis estimates show that hourly loads are far from being normally distributed and have fat tails. The sample kurtosis values range from 2.03 of American Electric Power (respondent ID 178) to 272.82 of Electric Board of Chattanooga (respondent ID 162).

Skewness is a measure of symmetry of the distribution of the observations. In the hourly load data sample, only 7 electricity providers have negative skewness whereas 47 electric entities have positive skewness. The positive values range from 0.03 (respondent ID 232) to 5.20 of Electric Board of Chattanooga (respondent ID 162). The positive sample skewness values of most of the providers indicate that hourly load observations are skewed right – the right tail is long relative to the left tail.

Table 4-3: Detail descriptive statistics of hourly load (GW) electricity providers that are available for most of the years during 2000 – 2012 period.

Reporting Agency Name	State	ID	Obs	Mean	St. Dev.	Skewness	Kurtosis	Min	Max
Alabama Electric Cooperative, Inc.	AL	101	96456	0.89	0.39	-0.34	3.51	0.00	2.38
PSO & SWEPCO	OH	110	96456	8.08	4.08	0.69	2.03	2.98	20.22
Arizona Public Service Company	AZ	116	94971	3.47	1.02	1.16	3.96	1.67	7.71
Associated Electric Cooperative, Inc.	MO	118	86758	2.19	0.56	0.81	3.44	0.00	4.54
Avista Corporation	WA	119	103367	1.42	0.26	0.60	3.65	0.00	2.55
Bonneville Power Administration	WA	122	103367	5.73	1.13	0.32	3.53	0.00	11.56
City of Burbank	CA	135	103367	0.13	0.04	1.26	11.02	0.00	1.14
City of Lafayette Utilities System	LA	138	96431	0.23	0.07	0.80	3.38	-0.12	1.06
Colorado Springs Utilities	CO	143	103366	0.53	0.09	0.25	2.98	0.00	0.90
Duke Energy Carolinas, LLC	NC	157	113976	11.19	2.31	0.73	3.48	0.00	20.63
East Kentucky Power Cooperative, Inc,	KY	159	105216	1.39	0.35	0.69	3.23	0.60	3.15
El Paso Electric Company	TX	160	103366	0.86	0.20	0.92	3.79	0.00	1.71
Electric Power Board of Chattanooga	TN	162	78888	0.68	0.17	5.20	272.82	0.23	10.54
Empire District Electric Co	MO	163	87610	0.60	0.15	0.78	3.46	0.00	1.20
EWEB (Eugene water and electric board)	OR	166	103731	0.30	0.06	0.35	3.10	0.00	0.57
Golden Spread Electric Cooperative, Inc.	TX	173	96455	0.52	0.29	0.94	3.73	0.00	1.58
Greenville Utilities Commission	NC	177	87673	0.19	0.05	0.81	3.53	0.00	0.37
Hawaiian Electric Company, Inc.	HI	178	96456	0.81	0.22	-0.05	1.92	0.00	1.31
Imperial Irrigation District	CA	182	103366	0.39	0.16	1.21	3.85	0.00	1.00
ISO New England Inc.	MA	185	61368	14.88	2.93	0.40	3.29	0.00	28.13
JEA	FL	186	96455	1.56	0.39	0.68	3.06	-0.28	3.34
Lincoln Electric System	NE	193	96392	0.39	0.09	0.97	4.16	0.00	0.79
	CA	194	103732	3.04	0.65	0.76	3.78	0.00	6.14
	LA	195	96432	0.12	0.03	0.82	3.12	0.00	0.25
Metropolitan Water District	CA	201	111715	0.20	0.09	-0.86	2.59	0.00	0.59
Modesto Irrigation District	CA	206	103732	0.29	0.08	1.40	5.44	0.00	0.71
Nebraska Public Power District	NE	209	89844	1.37	0.38	0.12	5.42	0.00	3.03
Nevada Power Company	NV	210	95337	2.69	0.88	1.28	4.14	0.00	6.33
New York Control Area	NY	211	105192	18.49	3.48	0.58	3.56	4.98	33.94
NYISO	NY	212	113971	1.78	0.30	0.24	3.00	-0.25	3.14
	MT	217	104097	1.10	0.27	-1.28	4.86	0.00	1.81
Oglethorpe Power	GA	218	113966	4.02	1.29	1.05	3.96	0.00	9.63
Ohio Valley Electric Corporation & Indiana-Kentuck	OH	219	96456	0.17	0.32	2.71	8.88	0.01	1.38
Oklahoma Municipal Power Authority	OK	221	96432	0.28	0.10	1.47	5.19	0.00	0.79
PJM	PA	230	113938	32.01	6.43	0.73	3.86	14.55	62.02
Portland General Electric Company	OR	232	103731	2.36	0.43	0.03	2.54	0.00	4.12
	CO	235	94606	4.24	1.02	0.25	3.00	-0.30	8.16
Public Service Company of New Mexico	MN	236	94972	1.14	0.24	0.60	3.39	0.00	2.02
PUD No. 1 of Chelan County	WA	237	103367	0.34	0.11	-0.48	2.65	0.00	0.67
Public Utility District No. 1 of Douglas County	WA	238	103731	0.15	0.04	0.90	4.00	0.00	0.38
Grant County	WA	239	103367	0.38	0.08	0.33	2.63	0.00	0.67
Puget Sound Energy	WA	240	94972	2.78	0.58	0.27	2.88	0.00	5.17
Sacramento Municipal Utility District	CA	243	103366	1.03	0.56	-0.30	3.04	0.00	3.28
Salt River Project Agric Imp & Power Dist	AZ	244	103366	3.15	0.98	1.02	3.61	1.50	6.79
San Diego Gas and Electric	CA	246	103367	2.36	0.49	0.39	3.20	0.00	4.69
Seattle City Light	WA	247	103367	1.13	0.21	0.07	2.67	0.00	1.90
Sierra Pacific Power Company	NV	249	112151	2.89	5.63	3.40	13.32	0.00	38.82
South Carolina Electric & Gas	SC	250	87670	2.77	0.60	0.82	3.28	0.00	5.37
Tennessee Valley Authority	TN	263	96432	19.32	3.52	0.63	3.24	0.00	33.48
Tucson Electric Power Company	AZ	266	103367	1.37	0.43	0.88	3.91	0.58	5.91
Turlock Irrigation District	CA	267	103366	0.25	0.08	1.08	4.60	0.00	0.61
United Illuminating Company	CT	268	71944	0.66	0.14	0.88	4.45	0.00	1.46
Western Area Power Administration-Lower Colorado	AZ	274	103367	1.14	0.35	-0.02	2.20	0.00	2.30

There are 16 unique respondents with hourly lambda observations available from year 2000. Average lambda values range from \$16.69/MWh (respondent ID 223) to \$46.06/MWh (respondent ID 170). The sample kurtosis value of all 17 respondents is greater than 3 – varying from 4.03 (respondent ID 277) to 179.28 (respondent ID 188) – suggesting that the distribution of observations have fat tails. The positive sample skewness values of 17 respondents indicate that the distribution of hourly lambda values have longer right tails than the left tails.

Table 4-4: Detail descriptive statistics of hourly load (\$/MWh) electricity providers and balancing authorities that are available for most of the years during 2000 – 2012 period.

Reporting Agency Name	State	ID	Obs	Mean	St. Dev.	Skewness	Kurtosis	Min	Max
City of Tallahassee	FL	140	87693	37.20	16.80	1.11	6.18	0.00	342.46
CLECO	LA	142	78912	38.46	23.53	1.38	4.44	0.00	154.86
Duke Energy Carolinas, LLC	NC	157	87672	32.72	16.07	3.80	32.78	0.00	328.09
Empire District Electric Co	MO	163	87668	41.65	19.15	1.18	5.94	0.00	290.40
Entergy Services, Inc	LA	164	96431	37.51	23.12	1.25	4.69	0.00	182.31
	FL	170	70153	46.06	26.96	6.29	177.89	0.00	1377.40
JEA	FL	186	105208	36.34	19.57	2.12	11.18	10.50	325.95
	MO	188	95702	22.34	20.22	5.22	179.28	-85.34	1300.00
New York Control Area	NY	211	96428	43.91	30.86	7.79	174.31	-296.85	1207.50
Omaha Public Power District	NE	223	78911	16.69	14.18	3.72	20.86	0.00	178.92
Progress Energy	FL	234	78912	43.94	30.46	3.15	37.08	0.00	1009.59
South Mississippi Electric Power Association	MS	252	70127	41.68	21.43	1.65	5.52	0.00	151.67
	AL	253	87647	40.56	20.33	2.86	20.67	0.00	510.64
Tennessee Valley Authority	TN	263	96433	34.09	21.52	2.15	14.09	0.00	330.00
Western Farmers Electric Cooperative	OK	277	105191	33.94	14.64	1.05	4.03	0.00	99.35

We use various diagnostic time-series plots in order to look at the nature of the observations. Particularly, we create symmetry plot, quantile plot of observation against the quantiles of uniform and normal distributions. Among various electricity providers and balancing authorities, we choose to show the diagnostic plots of PJM regions in figures 6 – 11.

Figure 6 is the symmetry plot of hourly load (GW) observations of PJM region during the period of 2000 – 2012. The dashed line indicates the symmetrical line (defined as y = x) where as the observed hourly loads are plotted in the graph. The figure shows that hourly load observations are above the reference line, far away from the median of the observations. It indicates that the distribution of hourly load of PJM region is skewed right. Similarly, we look at the nature of distribution with the help of quantile plots.

Figure 7 is the quantile plot of PJM's hourly load observations against the quantile of uniform distribution. Here, the graph plots each hourly load observation against the fraction of the data that have values less than that fraction. The diagonal dashed line is the reference line. Since the majority of values are below the reference line, the hourly load distribution is skewed right.

Miller (1997) recommends comparing distribution of data with normal distribution in order for detecting any nonnormality. This type of quantile plot focuses on tail of the distribution and helps us detect non-normality easily. In figure 8, we plot the quantile of PJM's hourly load against the quantiles of normal distribution. The grid lines in the graph indicate different percentile levels. We see that the distribution of hourly load is different than the dashed reference line, especially for the observations above 95 percentile. This graph confirms that hourly load observations at tails deviate significantly from the normal distribution.

Figures 9 – 11 give diagnostic plots of hourly lambda values of PJM region. The figures are similar to the hourly load observations; however show larger deviations from the reference lines. This suggests that nonnormality exist more in hourly lambda observations than hourly loads of PJM region. The time-series diagnostic plots of NYISO region are similar to the figures of PJM region. We include the figures of NYISO region – both hourly load and lambda values – in appendix.

Figure 4-6: Symmetry plot of hourly load (GW) observations of PJM region

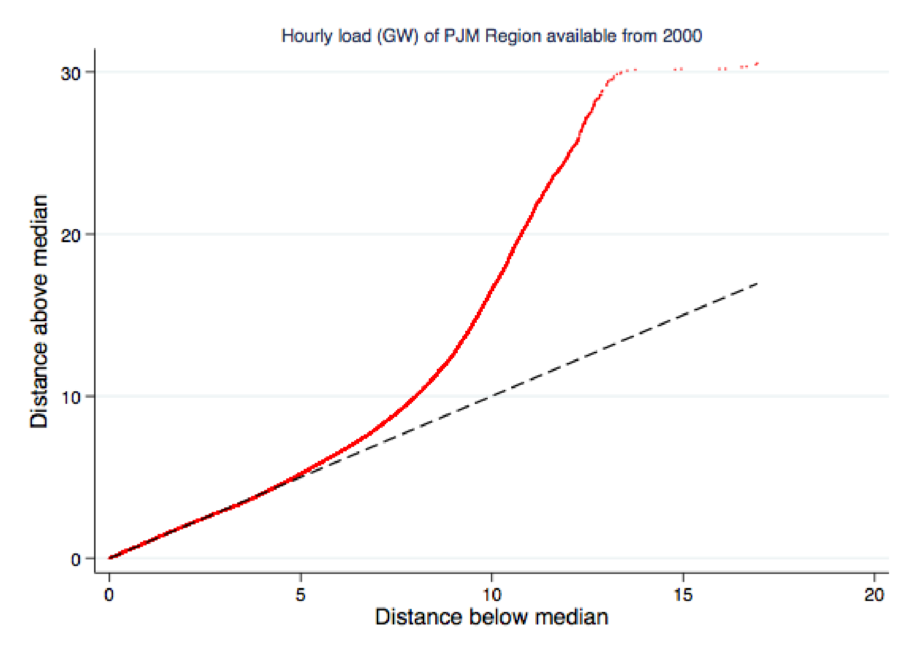


Figure 4-7: Quantile plot of PJM's hourly load against quantiles of Uniform distribution

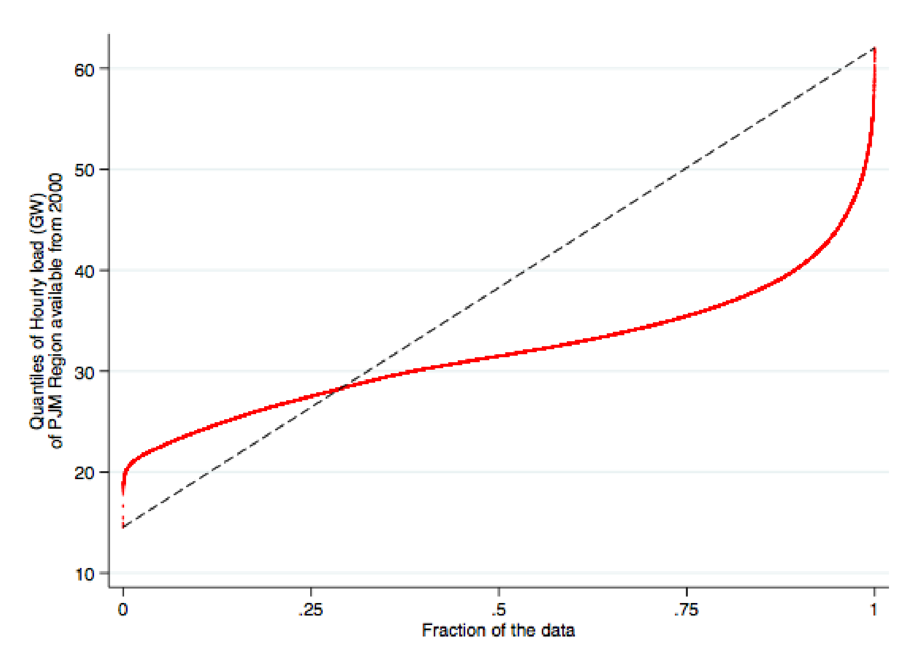


Figure 4-8: Quantile plot of PJM's hourly load (GW) observations against Normal distribution

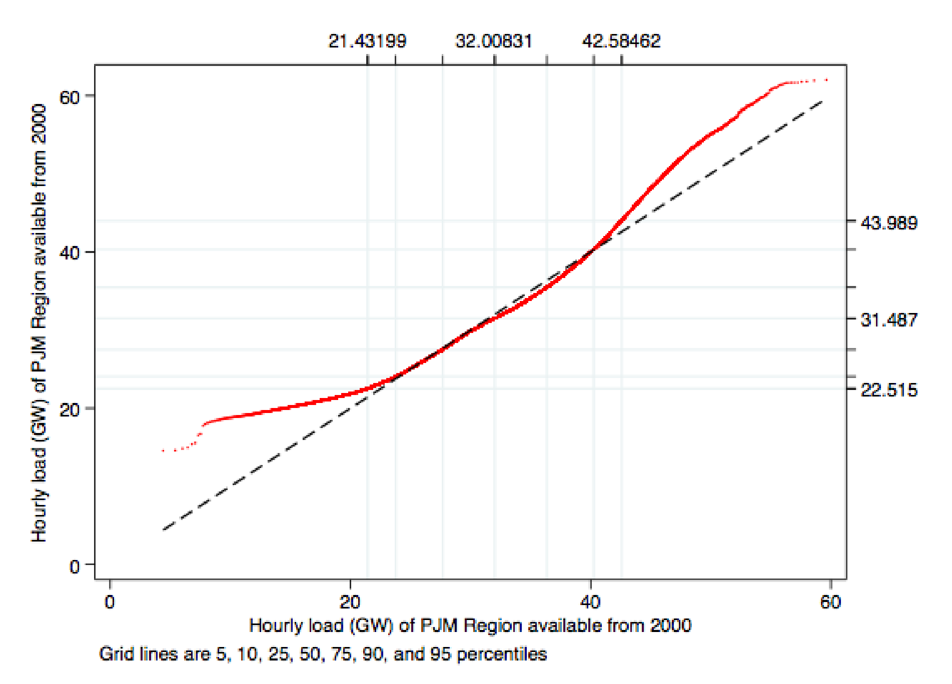


Figure 4-9: Symmetry plot of hourly lambda ($/MWh) observations of PJM region

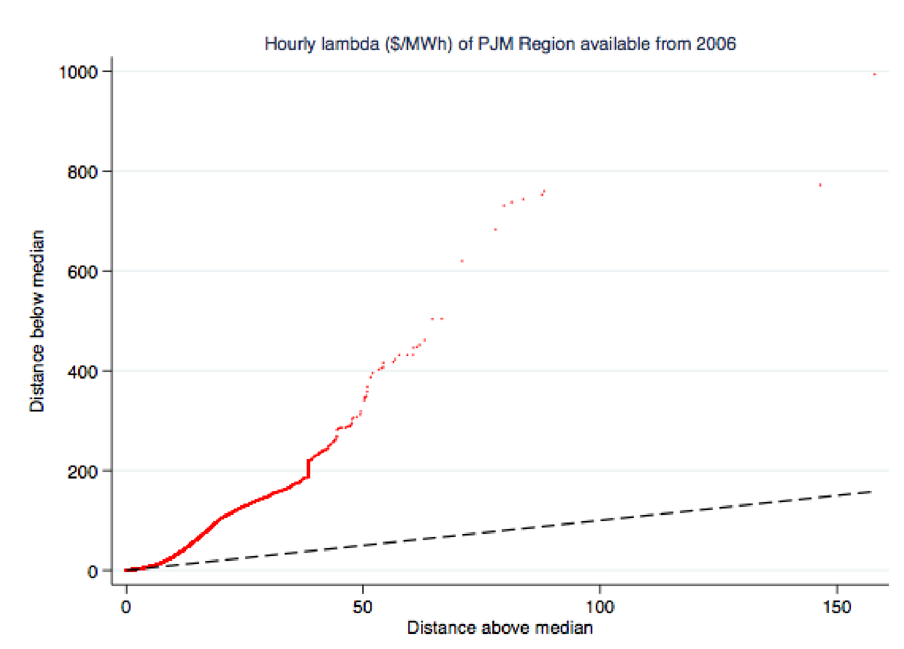


Figure 4-10: Quantile plot of PJM's hourly lambda ($/MWh) against quantiles of Uniform distribution

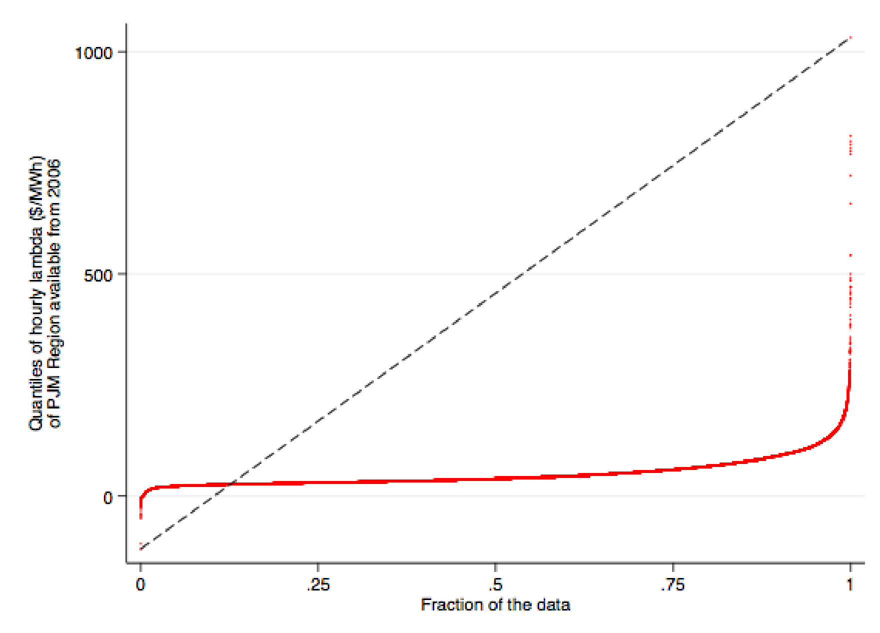
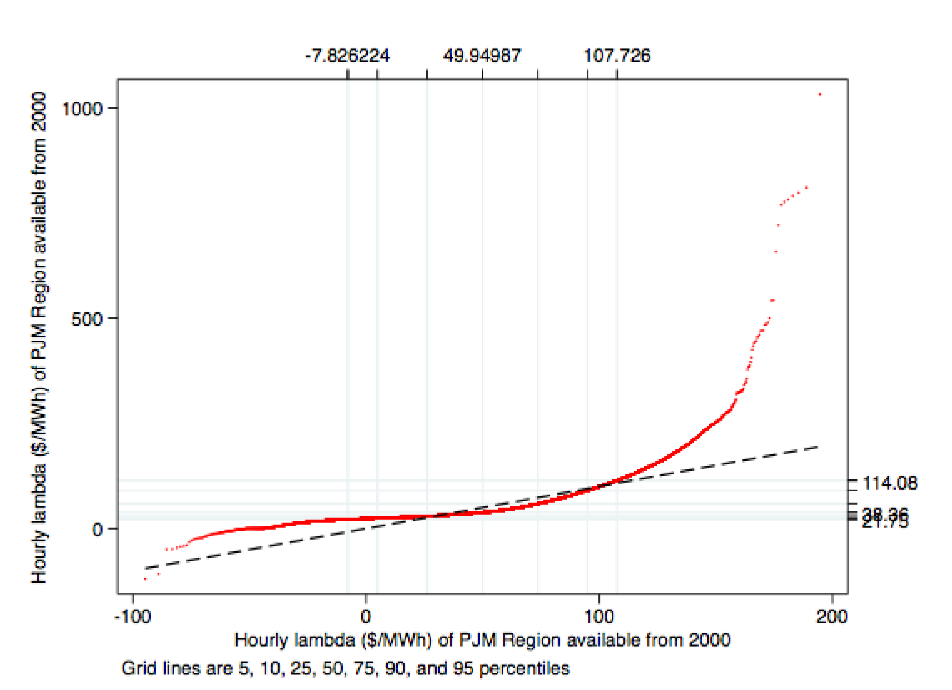


Figure 4-11: Quantile plot of PJM's hourly lambda ($/MWh) observations against Normal distribution



5. **Empirical Analysis**

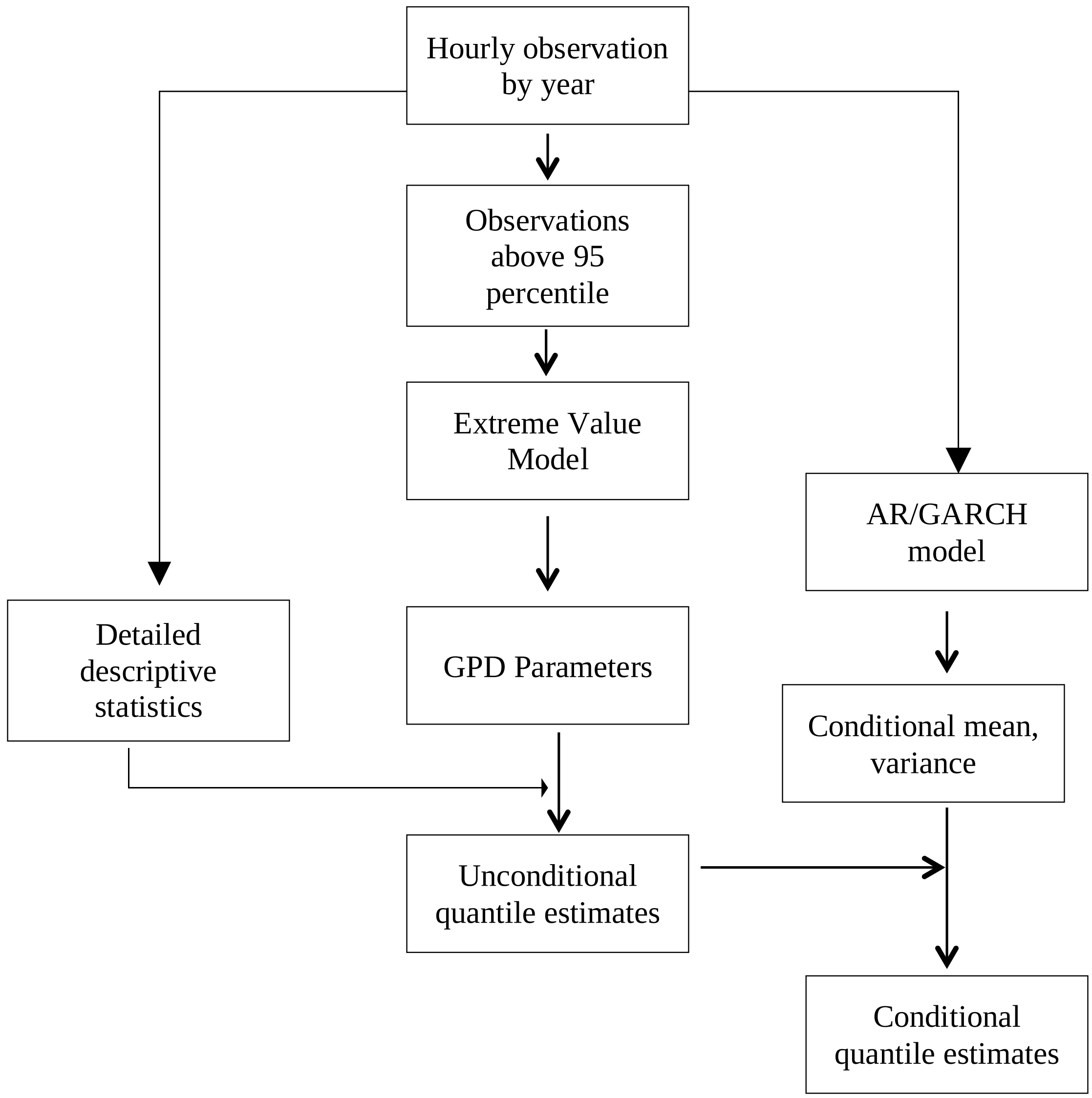
For empirical analysis of hourly load and lambda observations, we use three different types of results. They are generalized extreme value distribution parameters, AR/GARCH estimated predicted values, and detailed summary statistics. Besides analyzing how the parameters change between electric entities and geographic regions, we also use the parameters to calculate both unconditional and conditional tail quantiles. Figure 12 shows the process of calculating extreme value parameters and quantile estimates in a schematic diagram. We need GPD parameters and threshold level (95 percentile values in our case) to estimate unconditional quantiles. For conditional quantiles, we use conditional mean and variance estimated by AR/GARCH model and unconditional quantile estimates (see equations 18 and 21). All the result parameters vary by respondent ID and year.

We use *STATA*'s user-written code *gevfit* for the estimation purpose. STATA's default maximization technique is Newton – Raphson (NR) algorithm. However other techniques such as Bernd-Hall-Hall-Hausman (BHHH), Davidson-Fletrcher-Powell (DPF), and Broyden-Fletcher-Godlfarb-Shanno (BFGS) are also available. In *STATA*, if one technique does not help maximum likelihood estimates to converge, it switches to another method after five iterations. However, we can also specify the type of techniques and switching pattern. In order to make sure that the estimated generalized extreme value parameters are consistent, I also use *MATLAB* version of generalized extreme value distribution. Both *STATA* and *MATLAB* give exact same results. With the help of *STATA*'s *gevfit* command, we estimate location, scale, and shape parameters. In order to find the nature of the distribution, shape parameter is relevant.

Next, in order to address the time dependencies and volatility clustering observed in the electricity sector, we estimate AR/GARCH parameters with the help of *STATA*. The ARCH models seek to estimate the time-dependent volatility as a function of observed prior volatility (Stata Corp., 2013). GARCH models do not only account for the heteroskedasticity but also controls for the volatility clustering that are seen in the electricity sector. We use AR(1), AR(2), and AR(24) along with GARCH(1,1) to estimate variance, residuals, and predicted values of both hourly load and lambda values.[49] "Stata's ARCH command fits models of autoregressive conditional heteroskedacity using conditional maximum likelihood. The likelihood is conditional because it is computed based on an assumed or estimated set of priming values for the squared innovations and variances prior to the estimation sample" (Hamilton (1994) and Bollerslev (1986)).

[49] Matlab command for AR-GARCH models: arima('ARLags',1,'Variance',garch(1,1))

Figure 4-12: Flowchart of empirical analysis for estimating tail-quantiles of hourly load and lambda values



5.1 Shape Parameters across Geographic Regions

For the first set of analysis, we look at the average hourly load and lambda values of electricity entities by year and Census regions. In similar fashion, we also compare the average shape parameters obtained by fitting GEV model with the help of peak-over-threshold method. We are interested in analyzing shape parameters since they characterize the tail distributions of load and lambda observations.

Figure 13 gives the box plot of average load shape parameter (ξ) of electricity providers that are available for all years from 2000. The GPD model estimates a shape parameter using hourly annual observations. One of the benefits of generalized value distribution is that it allows data to decide the type of distribution. Most of the shape parameters of hourly load observations, 528 out of 589, are positive suggesting that the hourly load observations have Type II or Frechet value distribution. The annual average shape parameter varies between 0.154 – 0.433 during the period of 2000 – 2012. The median load shape parameter ranges from 0.143 – 0.218 during the same period.

Next, we look at how hourly load tail characteristics vary among US Census Regions. Figure 14 contains average load shape parameters of electricity providers by Census region. Among four Census regions, the average load shape parameter varies from 0.158 to 0.322 during the period of 2000 – 2012. The average load shape parameters of electricity providers of four Census regions are – Midwest: 0.322, Northeast: 0.300, West: 0.282, and South: 0.158. The figure shows that annual average shape parameters of electricity providers of Northeast and West regions are higher than Midwest and South regions. The high average shape parameters of West and Northeast regions suggest that their hourly load tail distributions are heavier than those of the Midwest and South regions.

In order to analyze the tail characteristics of hourly lambda observations, we utilize hourly lambda values of balancing authorities that are available for all years during 2006 – 2012. The average lambda shape parameter of balancing entities during 2006 – 2012 is 0.661 with the values ranging from 0.361 – 0.945. Almost all lambda shape parameters are positive indicating that lambda observations of balancing authorities have type II GEV distribution. We find that both load and lambda observations have type II GEV distribution. However, the magnitudes of lambda shape parameters are higher than load shape parameters. Figure 15 gives box-plot of average lambda shape parameters by year.

We plot average lambda shape parameters of electricity providers by Census region in Figure 16. The average shape parameter of all Census regions follow similar pattern. The graph shows that the annual lambda shape parameter of balancing authorities from West region is higher than other areas suggesting that hourly lambda values of West region's balancing authorities have larger extreme values compared with other regions' hourly lambda values.

Figure 4-13: Average annual load shape parameters for Electricity Providers. The electric entities are available for all years during 2000 – 2012 period.

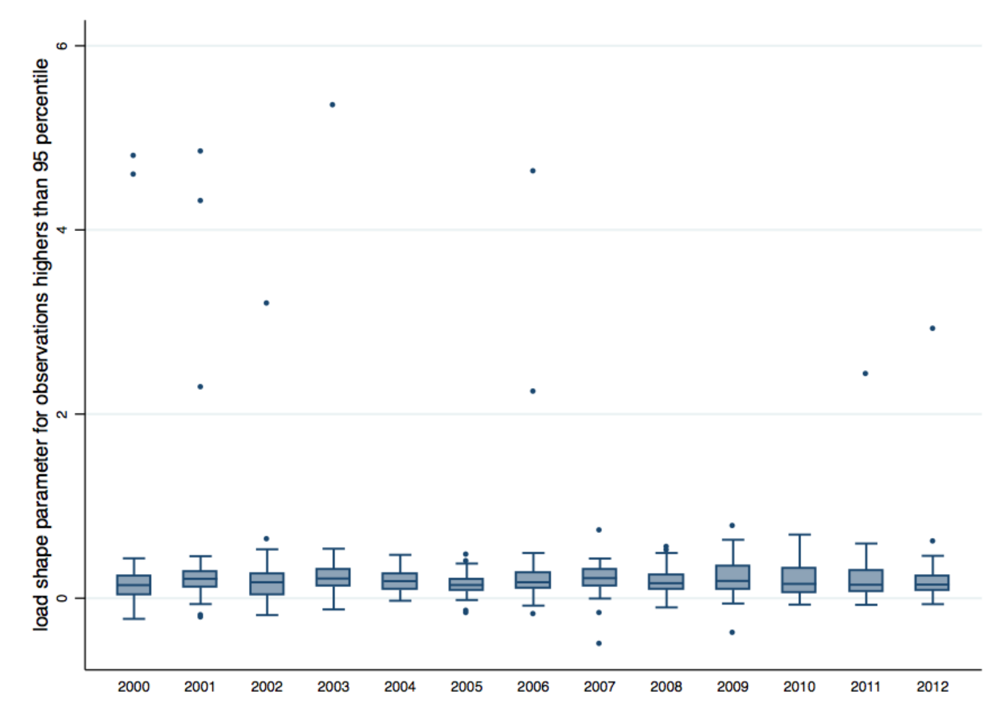


Figure 4-14: Average annual load shape parameters for Electricity Providers by Census regions. The electric entities are available for all years during 2000 – 2012 period.

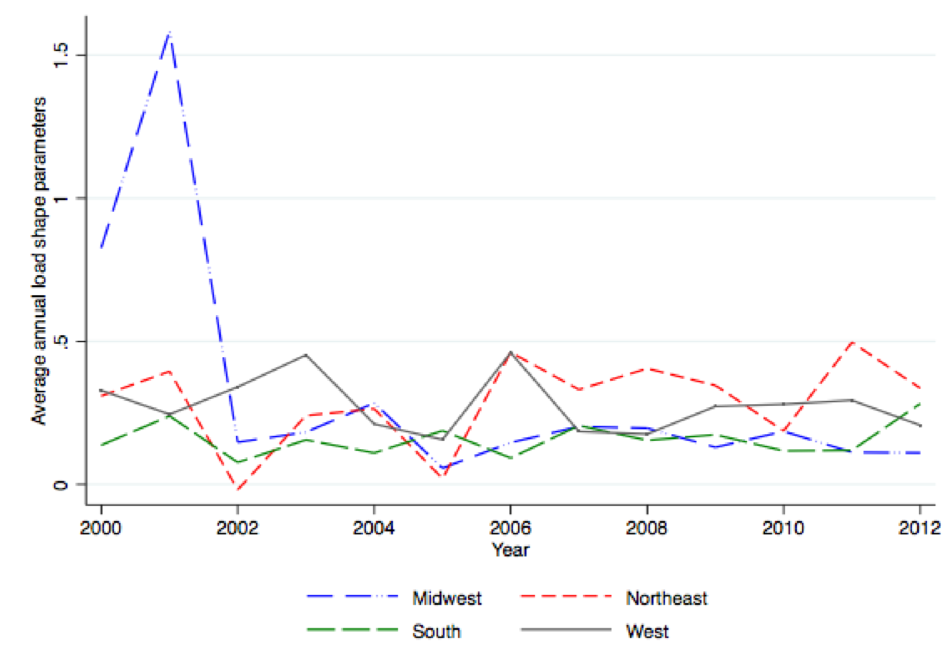


Figure 4-15: Average annual lambda shape parameter of Balancing Authorities. The electric entities are available for all years during 2000 – 2012 period.

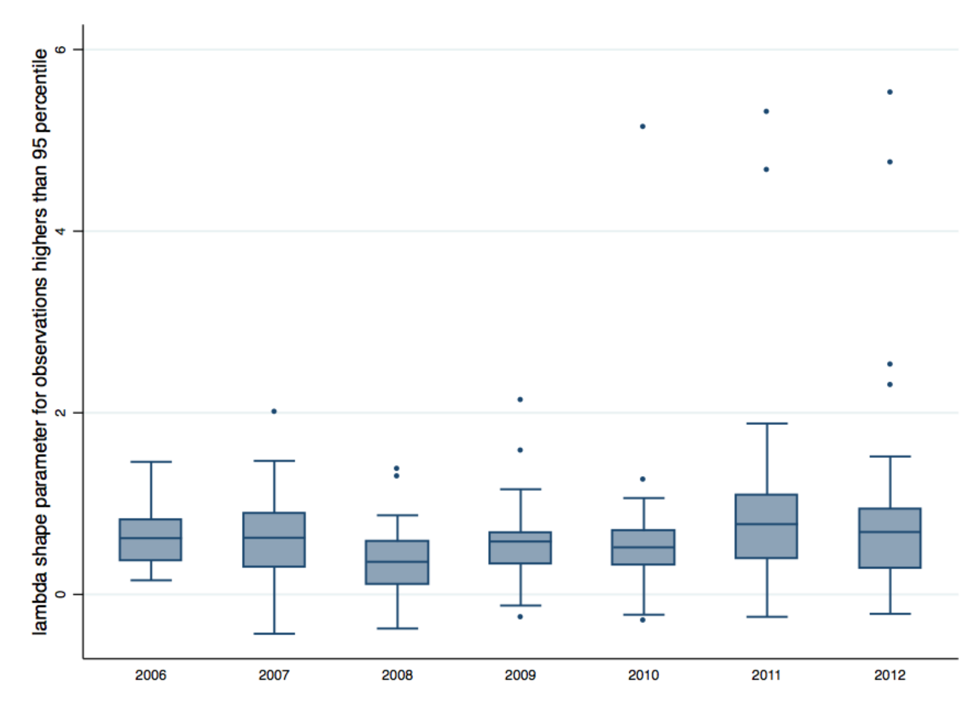
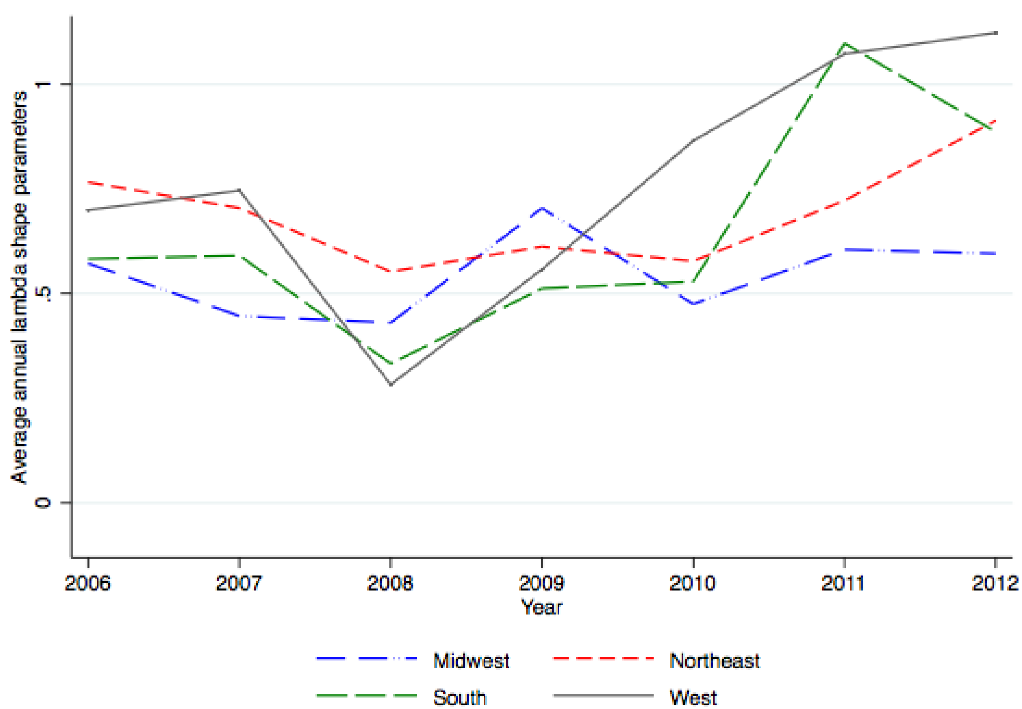


Figure 4-16: Average annual lambda shape parameter of Balancing Authorities by Census regions.The electric entities are available for all years during 2000 – 2012 period.



5.2 Estimating Tail Quantiles

We calculate tail quantiles of hourly electricity load and lambda with the help of generalized pareto distribution parameters. Use of extreme value theory to estimate extreme occurrences is of particular interest to utility and risk managers since the EVT methods better estimates than the models assuming hourly electricity data to have normal distributions. We discuss an example to estimate tail quantile based on Huisman (2009). In order to find hourly value that exceeds by 5% of all hours in a given year, we estimate 95% one-hour value-at-risk (VAR) such that

(22) $$\Pr(x > 95\%\, VAR) = 0.05$$

Using equations (8) and (17), we can wrie

(23) $$\Pr(x > 95\%\, VAR) = \frac{n_u}{n}\left(1 + \xi\frac{VAR - u}{\sigma_u}\right)^{-\frac{1}{\xi}} = 0.05$$

And rewriting the equation yields unconditional value-at-risk,

(24) $$VAR = u + \frac{\sigma}{\xi}\left(\left(\frac{n}{n_u}0.05\right)^{-\xi} - 1\right)$$

Besides unconditional value-at-risk, we also estimate two different quantiles using AR/GARCH models. First AR/GARCH quantile assumes error structures to be normally distributed, whereas the second one assumes the error terms to have student-t distribution. We also estimate quantiles at 99 percentile values (87 hourly observations in one year).

Tables 5 and 6 present average quantiles at 95 and 99 percentiles for hourly load observations of utilities, respectively. They only include the list of electricity providers that have data available continuously for 2000 – 2012 period. The first column gives the percentiles of actual observed hourly electricity demand. The second column is unconditional tail estimates using equation 8. Whereas, third and fourth columns give time dependencies corrected quantile values assuming Gaussian and student-t distributions for error terms in AR/GARCH model.

Table 5 shows that unconditional tail quantiles of hourly load have better estimates than AR/GARCH model at 95 percentiles. The unconditional tail quantiles are very similar to the observed hourly load data. The AR/GARCH quantiles underestimates the value-at-risk values at 95-percentile level, except in the case of Duke Energy, New York Control Area, PJM, and Tennessee Valley Authority. Similarly, table 6 suggests that unconditional method provide better tail quantile estimates than AR/GARCH models at 99 percentile level.

Table 4-5: Estimated hourly electricity load (GW) at 0.95 percentile

Respondent ID	Reporting Agency Name	State	95th Percentile	Unconditional	Conditional	Conditional - t
101	Alabama Electric Cooperative, Inc.	AL	1.279	1.279	0.936	0.946
110	PSO & SWEPCO	OH	11.022	11.022	10.360	10.459
116	Arizona Public Service Company	AZ	5.591	5.591	3.846	3.861
118	Associated Electric Cooperative, Inc.	MO	3.231	3.231	2.419	2.422
119	Avista Corporation	WA	1.793	1.793	1.432	1.433
122	Bonneville Power Administration	WA	7.343	7.343	6.620	6.605
135	City of Burbank	CA	0.202	0.202	0.132	0.132
138	City of Lafayette Utilities System	LA	0.364	0.364	0.237	0.236
143	Colorado Springs Utilities	CO	0.678	0.678	0.525	0.527
157	Duke Energy Carolinas, LLC	NC	15.626	15.626	15.856	16.008
159	East Kentucky Power Cooperative, Inc,	KY	1.991	1.991	1.545	1.544
160	El Paso Electric Company	TX	1.242	1.242	0.868	0.872
162	Electric Power Board of Chattanooga	TN	0.979	0.979	0.713	0.706
163	Empire District Electric Co	MO	0.893	0.893	0.619	0.619
166	Eugene water and electric board	OR	0.409	0.409	0.298	0.298
173	Golden Spread Electric Cooperative, Inc.	TX	0.909	0.816	0.535	0.534
177	Greenville Utilities Commission	NC	0.277	0.277	0.190	0.191
178	Hawaiian Electric Company, Inc.	HI	1.039	1.039	0.828	0.831
182	Imperial Irrigation District	CA	0.717	0.717	0.389	0.389
186	JEA	FL	2.290	2.240	1.665	1.667
193	Lincoln Electric System	NE	0.583	0.582	0.396	0.397
194		CA	4.228	4.227	3.331	3.360
195		LA	0.186	0.186	0.120	0.120
201	Metropolitan Water District	CA	0.278	0.085	0.195	0.196
206	Modesto Irrigation District	CA	0.455	0.455	0.285	0.286
209	Nebraska Public Power District	NE	2.065	2.065	1.447	1.448
210	Nevada Power Company	NV	4.557	4.557	2.973	3.012
211	New York Control Area	NY	24.786	22.696	27.516	29.145
212	NYISO	NY	2.276	2.275	1.887	1.897
217		MT	1.281	1.281	1.099	1.104
218	Oglethorpe Power	GA	6.587	6.586	5.008	5.117
219	Ohio Valley Electric Corporation & Indiana-Kentuck	OH	0.259	0.259	0.172	0.172
221	Oklahoma Municipal Power Authority	OK	0.507	0.507	0.300	0.307
230	PJM	PA	81.750	81.747	132.762	143.475
232	Portland General Electric Company	OR	3.041	3.041	2.489	2.503
235		CO	5.621	5.621	4.742	4.764
236	Public Service Company of New Mexico	MN	1.531	1.532	1.164	1.168
237	PUD No. 1 of Chelan County	WA	0.449	0.449	0.333	0.334
238	Public Utility District No. 1 of Douglas County	WA	0.227	0.227	0.150	0.150
239	Grant County	WA	0.491	0.491	0.377	0.377
240	Puget Sound Energy	WA	3.775	3.775	3.000	3.020
243	Sacramento Municipal Utility District	CA	1.810	1.810	1.398	1.383
244	Salt River Project Agric Imp & Power Dist	AZ	5.124	5.123	3.466	3.480
246	San Diego Gas and Electric	CA	3.149	3.149	2.548	3.225
247	Seattle City Light	WA	1.473	1.477	1.141	1.140
249	Sierra Pacific Power Company	NV	3.802	3.801	3.885	3.952
250	South Carolina Electric & Gas	SC	3.923	3.923	3.041	3.045
263	Tennessee Valley Authority	TN	25.782	23.509	30.272	29.880
266	Tucson Electric Power Company	AZ	2.104	2.104	1.403	1.405
267	Turlock Irrigation District	CA	0.397	0.396	0.251	0.252
274	Western Area Power Administration-Lower Colorado	AZ	1.553	1.558	1.163	1.207

Table 4-6: Estimated hourly electricity load (GW) at 0.99 percentile

Respondent II	Reporting Agency Name	State	99th Percentile	Unconditional	Conditional	Conditional - t
101	Alabama Electric Cooperative, Inc.	AL	1.421	3.380	1.012	1.030
110	PSO & SWEPCO	OH	12.209	11.725	10.495	10.599
116	Arizona Public Service Company	AZ	6.215	5.953	3.876	3.891
118	Associated Electric Cooperative, Inc.	MO	3.668	3.490	2.438	2.442
119	Avista Corporation	WA	1.934	1.882	1.435	1.436
122	Bonneville Power Administration	WA	8.057	7.800	6.688	6.672
135	City of Burbank	CA	0.243	0.227	0.132	0.132
138	City of Lafayette Utilities System	LA	0.408	0.389	0.237	0.237
143	Colorado Springs Utilities	CO	0.746	0.719	0.525	0.528
157	Duke Energy Carolinas, LLC	NC	17.519	16.721	16.185	16.347
159	East Kentucky Power Cooperative, Inc,	KY	2.256	2.162	1.558	1.557
160	El Paso Electric Company	TX	1.354	1.306	0.870	0.874
162	Electric Power Board of Chattanooga	TN	1.096	1.048	0.715	0.709
163	Empire District Electric Co	MO	1.018	0.964	0.621	0.620
166	Eugene water and electric board	OR	0.451	0.436	0.298	0.298
173	Golden Spread Electric Cooperative, Inc.	TX	1.026	0.873	0.536	0.535
177	Greenville Utilities Commission	NC	0.310	0.305	0.190	0.191
178	Hawaiian Electric Company, Inc.	HI	1.096	1.075	0.829	0.832
182	Imperial Irrigation District	CA	0.807	0.770	0.390	0.390
186	JEA	FL	2.518	2.375	1.671	1.674
193	Lincoln Electric System	NE	0.674	0.635	0.397	0.397
194		CA	4.902	4.644	3.368	3.401
195		LA	0.207	0.198	0.121	0.120
201	Metropolitan Water District	CA	0.281	0.085	0.195	0.196
206	Modesto Irrigation District	CA	0.544	0.507	0.286	0.286
209	Nebraska Public Power District	NE	2.249	2.177	1.451	1.453
210	Nevada Power Company	NV	5.125	4.895	2.998	3.040
211	New York Control Area	NY	28.307	24.669	28.307	30.077
212	NYISO	NY	2.519	2.427	1.894	1.905
217		MT	1.367	1.345	1.101	1.106
218	Oglethorpe Power	GA	7.504	7.094	5.085	5.201
219	Ohio Valley Electric Corporation & Indiana-Kentuck	OH	0.271	0.269	0.172	0.172
221	Oklahoma Municipal Power Authority	OK	0.594	0.555	0.301	0.310
230	PJM	PA	92.556	85.655	136.659	147.853
232	Portland General Electric Company	OR	3.300	4.069	2.555	2.571
235		CO	6.339	6.039	4.789	4.812
236	Public Service Company of New Mexico	MN	1.664	25.597	1.903	1.916
237	PUD No. 1 of Chelan County	WA	0.490	0.475	0.334	0.334
238	Public Utility District No. 1 of Douglas County	WA	0.263	0.251	0.150	0.150
239	Grant County	WA	0.534	0.516	0.378	0.377
240	Puget Sound Energy	WA	4.128	4.002	3.018	3.039
243	Sacramento Municipal Utility District	CA	2.350	2.133	1.484	1.466
244	Salt River Project Agric Imp & Power Dist	AZ	5.673	5.439	3.491	3.505
246	San Diego Gas and Electric	CA	3.584	3.427	2.571	3.293
247	Seattle City Light	WA	1.587	317.590	11.584	11.438
249	Sierra Pacific Power Company	NV	4.298	6.680	4.043	4.113
250	South Carolina Electric & Gas	SC	4.321	4.158	3.058	3.061
263	Tennessee Valley Authority	TN	28.337	24.888	30.921	30.504
266	Tucson Electric Power Company	AZ	2.334	2.237	1.407	1.410
267	Turlock Irrigation District	CA	0.464	0.436	0.252	0.252
274	Western Area Power Administration-Lower Colorado	AZ	1.686	77.827	5.324	34.453

Tables 7 and 8 present tail-quantile estimates of hourly lambda values at 0.95 and 0.99 percentiles. Even though, unconditional quantiles are comparable to the actual data, AR/GARCH model overestimates the tail quantiles. The work is underway to use hourly change in lambda values instead of lambdas in estimating tail quantiles. It makes sense to use actual hourly electricity load to calculate GPD parameters with the goal of finding extreme tail quantiles. Estimating extreme quantiles of hourly electricity load allows utility managers to plan infrastructures accordingly. However for electricity prices, risk managers or business owners are more interested in finding the extreme changes in hourly electricity prices so that they can reduce the risk associated with price fluctuations. The relevant literatures – Bystrom (2005), Gencay and Seluck (2004), McNeil and Frey (2000) – use price changes instead of actual price to estimate value-at-risk in financial, electricity, and emerging markets.

Table 4-7: Estimated hourly lambda ($/MWh) at 0.95 percentile

Respondent ID	Reporting Agency Name	State	95th Percentile	Unconditional	Conditional	Conditional - t
140	City of Tallahassee	FL	54.2	54.1	338.0	2310.6
142	CLECO	LA	67.7	18.3	314.8	1812.4
157	Duke Energy Carolinas, LLC	NC	46.5	9.2	86.9	204.9
163	Empire District Electric Co	MO	64.7	62.8	523.3	3404.0
164	Entergy Services, Inc	LA	63.5	63.5	791.5	6742.9
170		FL	82.2	82.1	1052.8	7540.0
172	Gainesville Regional Utilities	FL	63.0	63.0	2038.4	10797.9
186	JEA	FL	64.9	64.9	721.2	6393.5
188		MO	59.0	58.9	598.0	2107.0
211	New York Control Area	NY	78.2	78.2	1433.4	2267.8
223	Omaha Public Power District	NE	42.5	42.5	472.4	2529.0
234	Progress Energy (Florida Power Corp.)	FL	82.2	82.2	1382.3	6763.5
252	South Mississippi Electric Power Association	MS	69.7	61.9	843.1	5581.6
253		AL	73.5	73.5	684.5	4101.7
263	Tennessee Valley Authority	TN	67.3	67.2	435.5	3662.1
277	Western Farmers Electric Cooperative	OK	50.7	50.7	129.5	1016.2

Table 4-8: Estimated hourly lambda ($/MWh) at 0.99 percentile

Respondent ID	Reporting Agency Name	State	99th Percentile	Unconditional	Conditional	Conditional - t
140	City of Tallahassee	FL	64.9	61.0	370.2	2536.0
142	CLECO	LA	76.2	20.4	347.8	2017.6
157	Duke Energy Carolinas, LLC	NC	84.5	2592.4	14587.1	34868.4
163	Empire District Electric Co	MO	80.9	75.5	617.9	3994.0
164	Entergy Services, Inc	LA	73.1	68.8	849.1	7249.9
170		FL	118.2	109.4	1378.7	9860.1
172	Gainesville Regional Utilities	FL	77.9	72.9	2355.0	12547.8
186	JEA	FL	88.5	81.3	887.9	7902.9
188		MO	80.8	75.3	759.5	2717.9
211	New York Control Area	NY	128.3	119.9	2159.0	3618.1
223	Omaha Public Power District	NE	60.1	58.0	605.2	3174.6
234	Progress Energy	FL	119.6	105.8	1758.5	8636.8
252	South Mississippi Electric Power Association	MS	79.2	67.3	897.3	6038.5
253		AL	96.8	90.2	831.0	5003.5
263	Tennessee Valley Authority	TN	87.9	81.9	525.8	4471.5
277	Western Farmers Electric Cooperative	OK	57.9	55.3	138.7	1115.6

6. Conclusion

We present a simple way to estimate extreme value occurrence with the help of extreme value theory. Extreme value method allows focusing on fat tails of electricity demand and prices without needing to worry about fitting all hourly observations to a single distribution. The extreme value theory is very efficient tool for utility and risk managers to estimate extreme occurrences at different percentile levels.

The goal of this paper is to provide a comprehensive analysis of extreme tail characteristics of different market regions' hourly electricity load and prices. We estimate annual extreme value parameters of both hourly electricity load and lambda with the help of peak-over-threshold method. The threshold level is fixed at 95 percentile levels, allowing us to use 438 observations (0.05*8760) in the estimation process. In order to be consistent with our analysis, we only use electric entities that have hourly data available continuously during 2000 – 2012. We compare shape parameters of different electric entities individually and then by geographic regions. Then, we use extreme value parameters to predict the return value – the maximum value that the electricity price or load can reach in future – at different percentile values. Besides unconditional return values, we also estimate tail quantiles after addressing time dependencies with the help of AR/GARCH models.

Our results indicate that the distributions of hourly load and lambda values are fat tailed. Hourly lambda values have more extreme values generating fatter tails than hourly electricity load. This is understandable because hourly load have upper limit due to physical constraints such as transmission lines and generation capacity. We also estimate single-point extreme tail quantiles with the help of generalized pareto distribution parameters. We show that unconditional extreme quantiles are very similar to the actual observed load at both 95 and 99 percentile levels. The conditional quantiles are quite comparable for hourly load values. However, hourly lambda extreme quantile calculated after correcting for time dependencies overestimates than the actual hourly lambda values. Estimating tail quantiles of hourly electricity price change is more relevant research question than estimating quantiles of hourly lambda values.

For planning purposes, it would make sense to use actual hourly electricity load to calculate GPD parameters with the goal of finding extreme tail quantiles. However for electricity prices, risk managers or business owners are more interested in finding the extreme changes in hourly electricity prices so that they can reduce the risk associated with price fluctuations. The relevant literatures – Bystrom (2005), Gencay and Seluck (2004), McNeil and Frey (2000) – use price changes instead of actual price to estimate value-at-risk in financial, electricity, and emerging markets.

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8. Appendix

Figure 4-17: Symmetry plot of hourly load (GW) observations of NYISO region

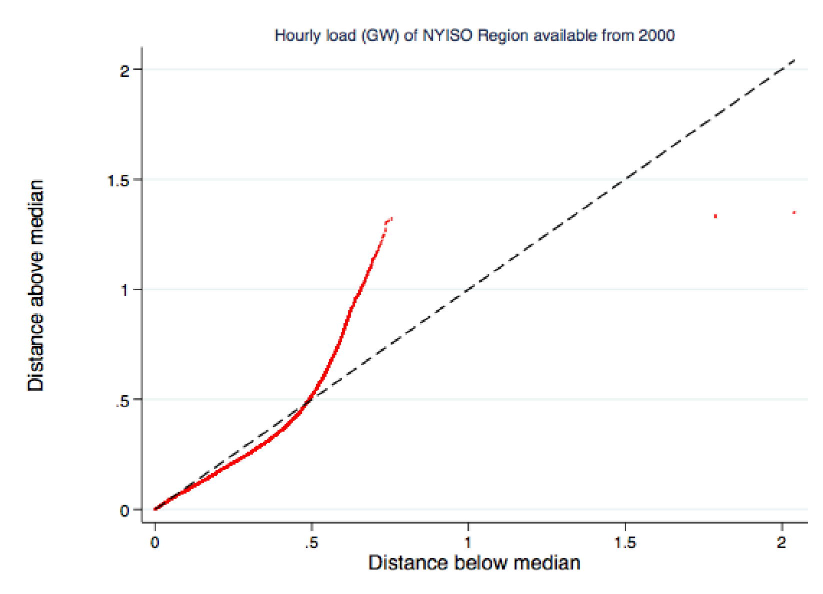


Figure 4-18: Quantile plot of NYISO's hourly load against quantiles of Uniform distribution

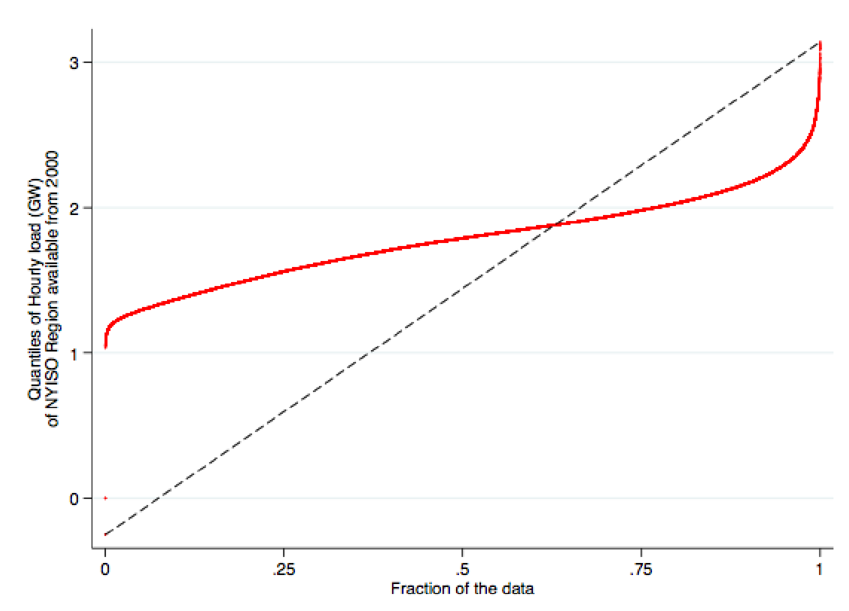


Figure 4-19: Quantile plot of NYISO's hourly load (GW) observations against Normal distribution

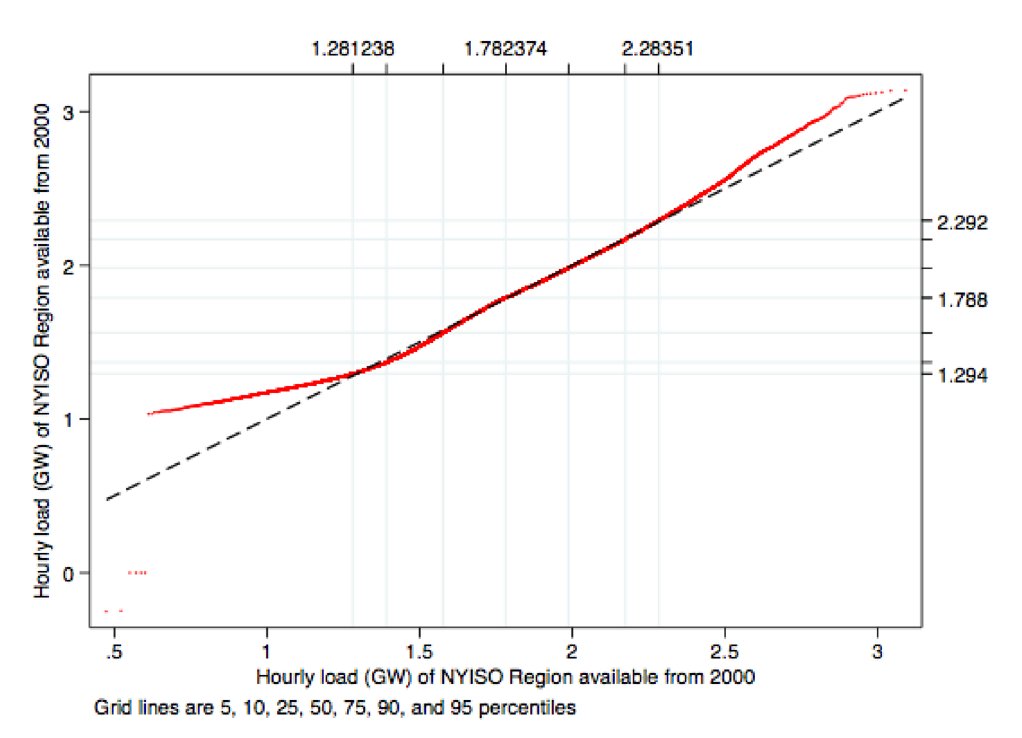


Figure 4-20: Symmetry plot of hourly lambda ($/MWh) observations of NYISO region

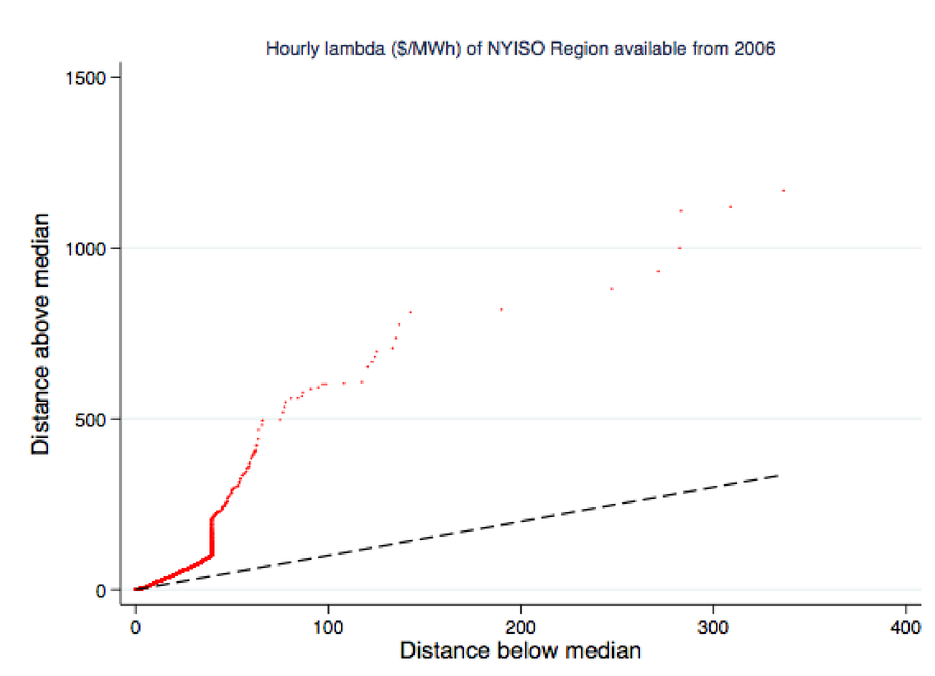


Figure 4-21: Quantile plot of NYISO's hourly lambda ($/MWh) against quantiles of Uniform distribution

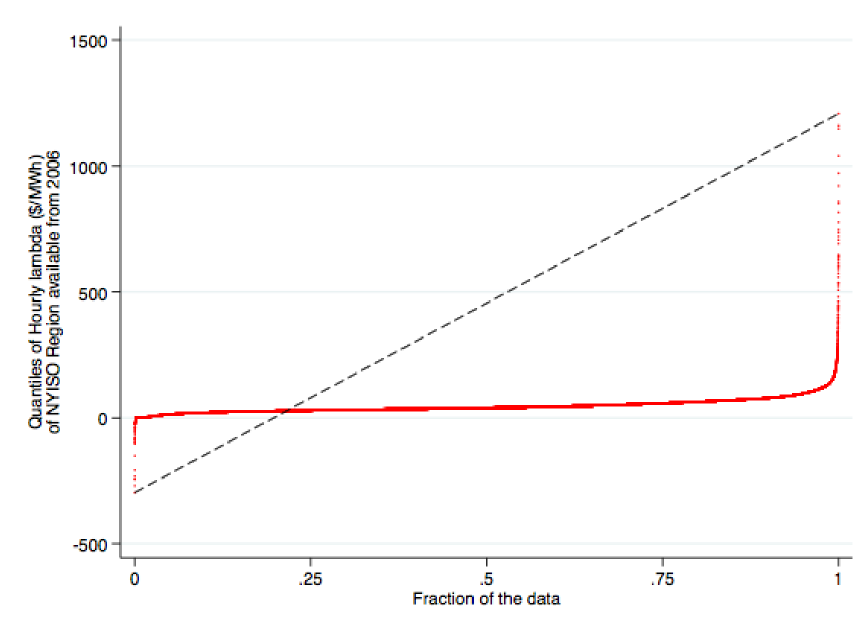


Figure 4-22: Quantile plot of NYISO's hourly lambda ($/MWh) observations against Normal distribution

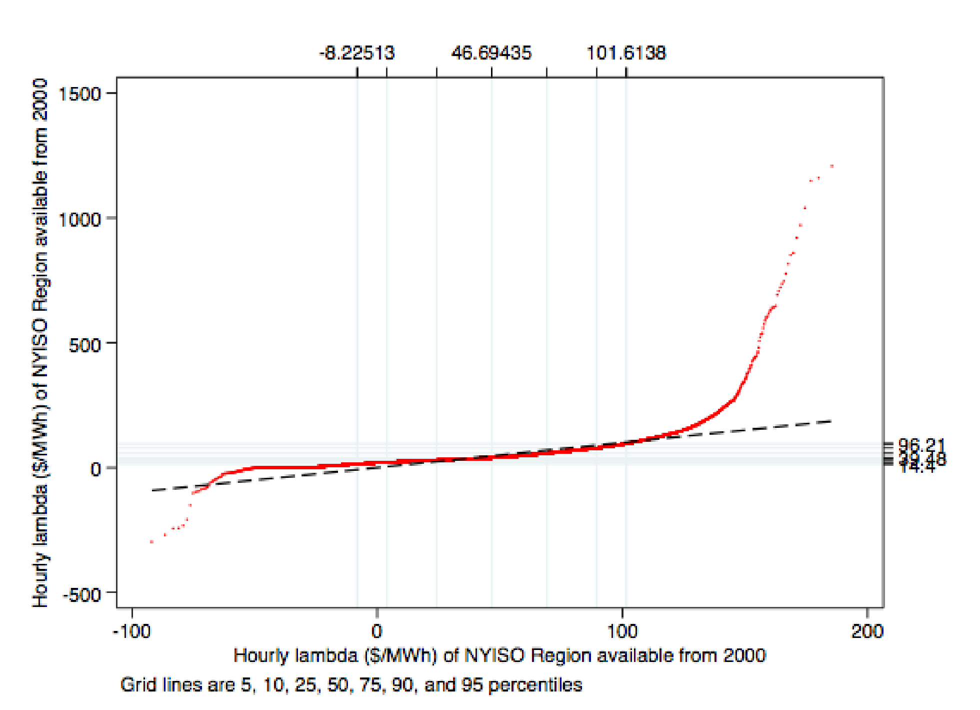


Figure 4-23: Average annual load (GW) of Electricity Providers. The electric entities are available for all years during 2000 – 2012 period.

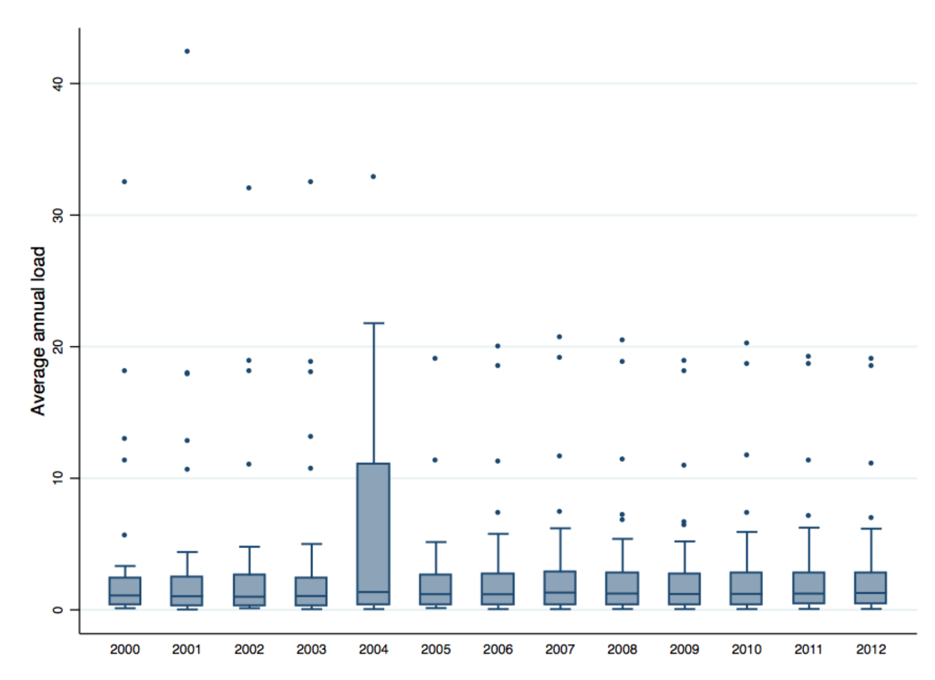


Figure 4-24: Average annual load (GW) of Electricity Providers by Census regions. The electric entities are available for all years during 2000 – 2012 period.

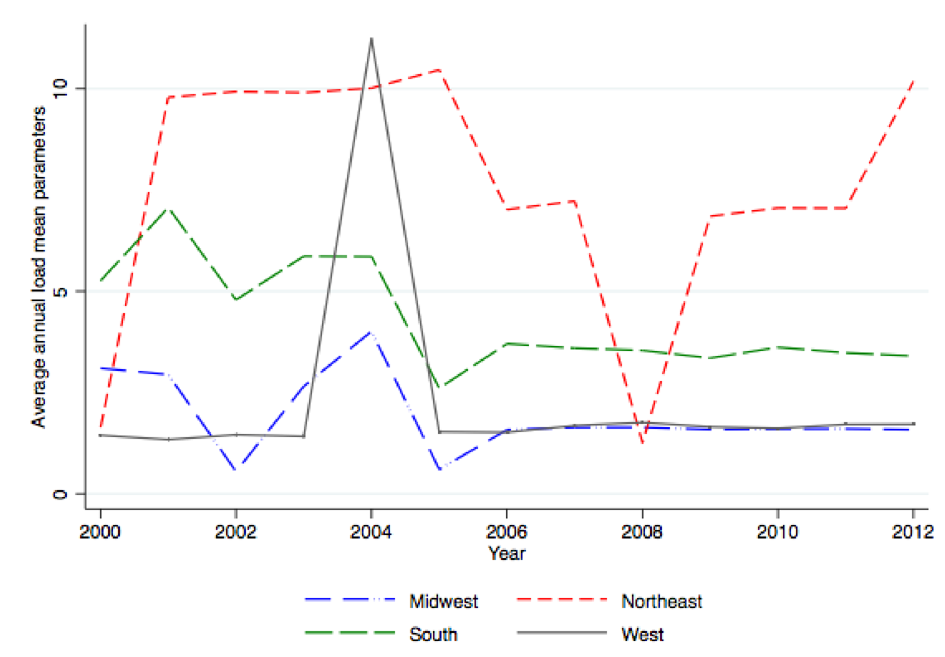


Figure 4-25: Average annual lambda ($/MWh) of balancing authorities. The electric entities are available for all years during 2006 – 2012 period.

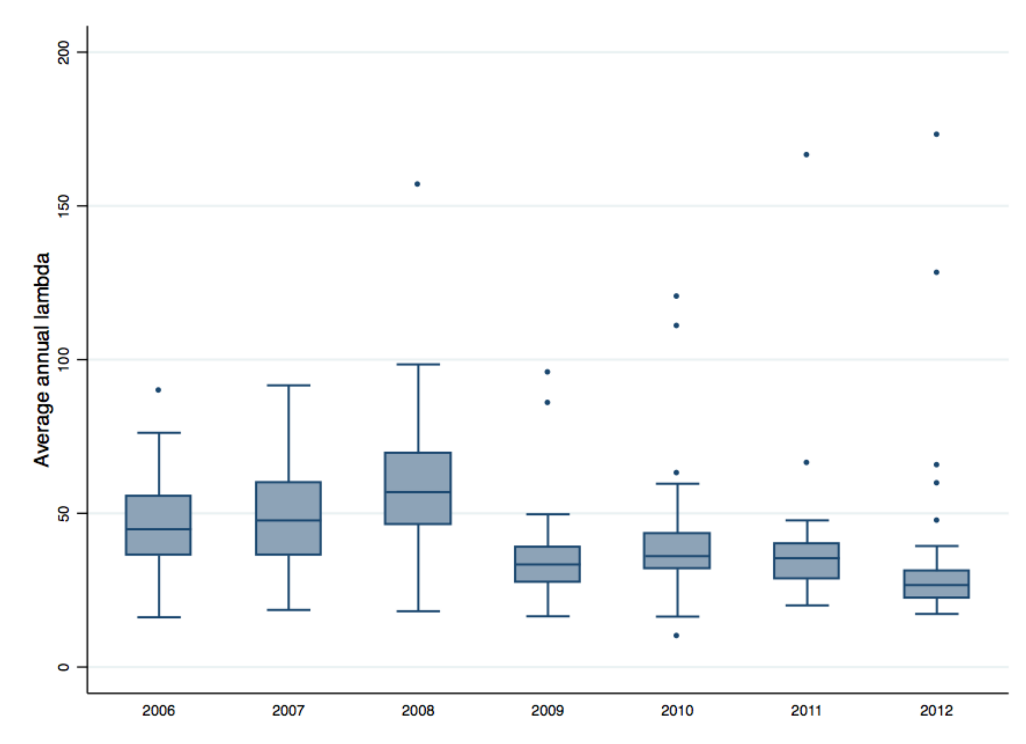
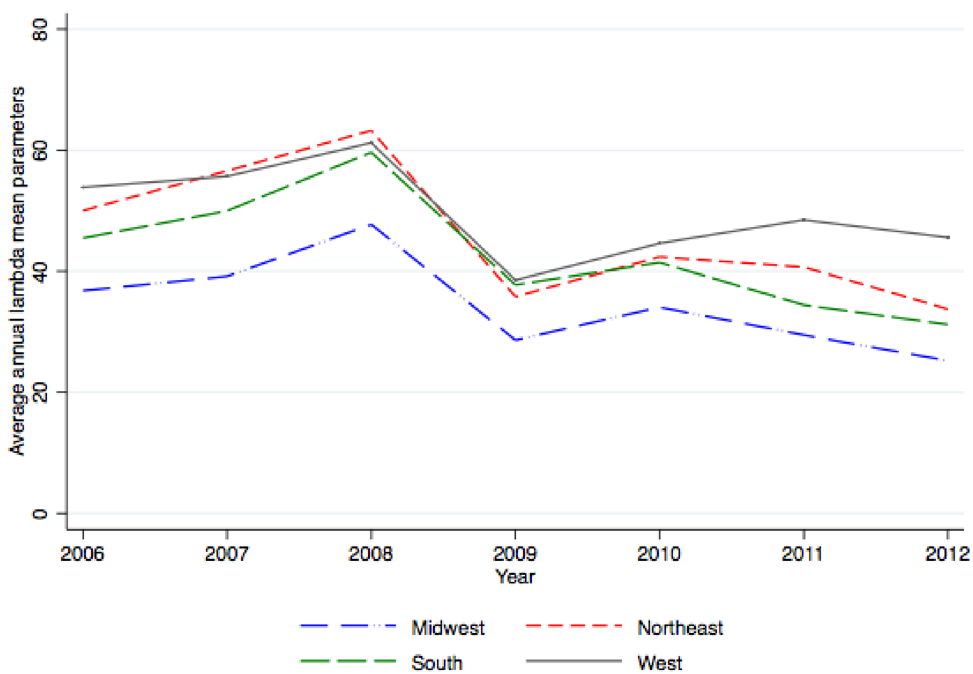


Figure 4-26: Average annual lambda ($/MWh) of balancing authorities by Census regions. The electric entities are available for all years during 2006 – 2012 period.



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