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ESSAYS ON DEMAND RESPONSE AND A SUPPLY CHAIN MODEL FOR A VERTICALLY INTEGRATED OIL COMPANY

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ABSTRACT

When electricity demand is at or near its highest level, more expensive and less efficient generators have to be dispatched by the system operator in order to meet the additional peak demand. The utilization of these units results in higher generating costs that translates into higher wholesale electricity prices. In some markets within the United States wholesale prices can fluctuate from less than 5 cents per kWh to as much as 30 cents per kWh. Under these circumstances, even a small decrease in electricity demand can result in a significant reduction in wholesale and aggregate end-user prices. In order to achieve these reductions, peak consumption electricity prices can be changed over time in such a way that they reflect wholesale prices more closely. Assuming that electricity customers are price responsive, customers would react to this variation in prices by changing their consumption patterns. This reaction to changes in electricity prices is known as Demand Response (DR).

Although several pilot studies have found evidence of customers' responsiveness to price signals, the reported levels of response to similar changes in price are still variable; making price-based DR programs an unreliable model for dealing with system contingencies and planning. However, as more data becomes available, it will be possible to have a more accurate understanding of the potential for broader implementation of Economic DR programs.

Using data from a pilot study carried out by Green Mountain Power (GMP) as a component of the eEnergy Vermont Smart Grid project in Rutland, VT I performed a series of studies that seek to provide evidence of changes in electricity demand due to price signals. The proposed dissertation is organized as follows:

Chapter 2 of this thesis provides more details on the origins, legislation and current status of demand response in the United States, including a review of the current literature on dynamic pricing that shows different methodological trends. Additionally, I examine five Consumer Behavior Studies (CBS) funded by the Smart Grid Investment Grant (SGIG). The studies analyze

different dynamic tariffs and some of them discuss the importance of enabling technologies. Research shows that customers do respond to dynamic pricing. However, more evidence is needed in order to assess the persistence of these responses.

Chapter 3 provides an impact analysis of a residential DR pilot study carried out by Green Mountain Power in the city of Rutland, Vermont. This analysis provides evidence of reductions in electricity demand during critical peak events due to price signals.

In Chapter 4 I estimate the relative impact of socioeconomic factors on households' electricity consumption patterns. I use a Descriptive Factor Analysis (DFA) to group previously measured variables that are used as a predictor of electricity consumption. Results of this analysis indicate that, among the measured predictors, number of air conditioners, ceiling fans and people living in the household, have the biggest influence in determining customer responsiveness to price signals during critical peak events.

Chapter 5 is a survival analysis of the GMP pilot program. The obtained evidence suggests that attempting to change customers from the Critical Peak Rebate (CPR) to the Critical Peak Pricing (CPP) treatment group appears to have a dramatic effect on drop-out rates. Additionally, providing households with an in-home display reduces by three times the risk of dropping out when facing the possibility of transitioning from a CPR to a CPP tariff. Also, receiving and in-home display had a significant effect on households enrolled in the CPP group. The obtained hazard rate for the Critical Peak Pricing with in-home display (CPP-I) group is half that of the CPP group.

Finally, chapter 6 presents a model for supply chain planning of a vertically integrated oil company. The developed model maximizes the utility of a vertically integrated oil company including multimodal transportation, subsidiaries, and financial metrics. This tool reduces the discontinuity of the operational planning process and allows the vertically integrated oil company to take the best optimization decisions taking into consideration risks associated to potential affections of the oil transport infrastructure.

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Chapter 1

Introduction

When electricity demand is at or near its highest level, more expensive and less efficient generators have to be dispatched by the system operator in order to meet the additional peak demand. The utilization of these units result in higher generating costs that translates into higher wholesale electricity prices. In some markets within the United States wholesale prices can fluctuate from less than 5 cents per kWh to as much as 30 cents per kWh. Under these circumstances, even a small decrease in electricity demand can result in significant reductions in wholesale and aggregate end-user prices. In order to achieve this reduction, peak consumption electricity prices can be changed over time in such a way that they reflect wholesale prices more closely. Assuming that electricity customers are price responsive, customers would react to this variation in prices by changing their consumption patterns. This reaction to changes in electricity prices is known as Demand Response (DR).

Demand response programs can be categorized as either Incentive-Based DR programs or Economic (Price-Based) DR programs (FERC, 2012). Incentive-Based programs may include Obligated/Voluntary Load Curtailment, Demand Bidding, Direct Load Control/Cycling, and the ancillary services market. Customers participating in Incentive-Based programs receive participation payments in the form of a bill credit or a discount rate (Albadi, 2008). Price-Based DR programs include time-varying electricity rates like Critical Peak Pricing (CPP), Critical Peak Rebates (CPR), and Real Time Pricing (RTP) (Walawalkar, 2010). Demand Response program types are shown in Table 1.1.

Under Load Curtailment programs and Load Control/Cycling programs, equipment like air conditioners and water heaters are remotely or manually controlled. Customers participating in these programs receive upfront incentive payments and can face penalties if they do not respond adequately to notices. Under Demand Bidding programs, customers are allowed to bid on specific load reductions in the wholesale market. Bids are accepted according to the market's marginal price and once accepted customers have to commit to these reductions or face penalties.

Table **1-1**: Demand response program types (FERC, 2012).

Incentive-Based Programs	Price-Based Programs
Demand Bidding Buyback	Critical Peak Pricing with Control
Direct Load Control	Critical Peak Pricing
Emergency Demand Response	Peak Time Rebate
Interruptible Load	Real-Time Pricing
Load as Capacity Resource	Time-of-Use Pricing
Non-Spinning Reserves	System Peak Response Transmission Tariff
Regulation Service	
Spinning Reserves	

Economic DR tariffs are based on time varying tariffs that, contrary to flat rates, reflect the real marginal cost of electricity generation more closely. The objective of these tariffs is to reduce consumption during periods of high demand, thereby lowering the overall system marginal cost. Under Critical Peak Pricing users face higher electricity prices during hours of higher demand. These periods usually coincide with extreme high or low temperatures, and customers are notified of them the day before the event takes place. Critical Peak Rebate programs follow a similar logic, but instead of charging higher prices during critical events, customers are charged lower prices if they consume less than a predefined threshold during those periods.

Under Real Time Pricing, users are charged hourly prices that are proportional to the marginal cost of the system at any given time. This tariff involves the use of enabling technologies like In-Home Displays (IHDs) to provide customers with day-ahead or hour-ahead electricity prices. CPR and CPP rates can also be complemented with enabling technologies, but the use of these technologies is not vital for the implementation of these tariffs. In addition to

IHDs, enabling technologies include Programmable Communicating Thermostats (PCTs), Energy Orbits, and onsite generation units. CPR and CPP tariffs can also be complemented with Time-of-Use Tariffs (TOU), which are block rates that emulate the variation of the system marginal cost over the course of the day. These tariffs are fixed and usually consist of two time blocks – peak and off-peak periods.

Customers participating in Price-Based DR programs can realize bill savings by consuming less electricity during periods of aggregated peak demand. Customers can respond to price signals by taking different actions. First, they can reduce electricity demand during peak periods by moving electricity intensive activities such as doing laundry or cooking to off-peak periods. Secondly, customers can reduce the usage of air conditioning or heaters in periods of extreme temperatures (this option implies a loss of comfort but does not imply load shifting to other periods). Finally, consumers can use on-site generation during peak hours. In the case of residential customers, this implies the use of solar panels or batteries that store electricity during off-peak periods so that it can be used during peak periods. This option may not result in significant reductions in overall consumption, but it can definitely impact peak consumption patterns and result in lower wholesale electricity prices.

Although several pilot studies have found evidence of customers' responsiveness to price signals, the reported levels of response to similar changes in price are still variable; making price-based DR programs an unreliable model for dealing with system contingencies and planning. However, as more data becomes available, it will be possible to have a more accurate understanding of the potential for broader implementation of Economic DR programs.

Multiple potential benefits are associated with the adoption of DR programs. Participants can benefit from lower electricity prices during peak periods which produce savings in their electricity bills (depending on their consumption patterns). The market as a whole could benefit from DR programs by avoiding the dispatch of the last less efficient and more expensive generator and by delaying the expansion of infrastructure related to increments in peak load. Benefits could also include increased reliability due to decreased system contingencies. Market power may be diminished by taking away the ability of an expensive marginal plan to significantly alter the overall system generating cost. Finally, if a persistent response to price signals is achieved, it may result in decreased required reserve margins. Reserve capacity is proportional to the highest consumption peak and can equal as much as 15% of total installed capacity (Faruqui, 2006). Thus, a reduction in peak consumption would not only defer the addition of more peaking plants but would also defer the introduction of more operational reserves.

Chapter 2

Demand Response: A Review

Background

Demand Response (DR) has been recognized as a valuable instrument for providing electricity customers with the necessary tools to react to changes in wholesale electricity prices that take place during periods of high consumption associated with extreme weather and other factors. Demand Response programs are generally classified into two categories: Incentive-Based and Economic-Based demand response programs. Incentive-Based programs offer customers payments in the form of bill credits in exchange for putting part of their electricity consumption capacity at the disposal of the system. Incentive-Based programs represent almost 80 percent (38,000 MW) of potential peak load reduction. The most broadly adopted types of incentive-based programs are Load as a Capacity Resource, Direct Load Control, and Interruptible Load. Economic-Based programs provide customers with price signals that seek to induce changes in consumption patterns during periods of high demand. Economic-Based DR programs include Real Time Pricing (RTP), Critical Peak Pricing (CPP), and Critical Peak Rebate (CPR) tariffs. Although potential peak load reductions in Economic-Based programs are considerably smaller than those estimated for Incentive-Based programs, it is estimated that they can provide up to 2,700 MW for peak load reductions (Cappers, 2009).

History of demand response

Demand response has been around for a long time. As early as the mid-1890s, system engineers and utility executives debated how to price this new service (Cappers, 2009). In 1934, Detroit Edison started using water heaters to manage load (Fanney and Dougherty, 1996). However, demand response and energy efficiency programs became more popular in the 1970s in response to increased fuel prices and growing demand for electricity. The mid-1990s saw a wave of restructuring in several U.S. electricity markets, mainly focused on the supply side of the system. The introduced changes were intended to lower the market power exercised by regional monopolies. Among the reforms introduced were the de-integration of vertically integrated utilities, the introduction of wholesale electricity markets, the establishment of independent system operators, and open access to transmission services for independent electricity retailers. A decade after the restructuring took place; a crisis hit the California electricity market. Manipulations of the wholesale market resulted in price spikes. Market participants were able to restrict output from base and shoulder generators in order to force the dispatch of more expensive peak generators. Thus, they got paid a higher marginal price at the wholesale market. This problem led to the reversal of many of the previously introduced reforms. It also led policymakers to realize the important role that Demand Response programs could play to reduce market power and to improve the overall efficiency of wholesale electricity markets (Faruqui 2006).

DR Legislation

The first piece of legislation intended to expand the penetration of DR programs in the U.S. was the 2005 Energy Policy Act. This policy included a mandate for the Federal Energy Regulatory Commission (FERC) to: 1) carry out an assessment of electricity DR resources available on national level and 2) to eliminate any unnecessary barriers to the participation of demand response resources in energy, capacity, and ancillary service markets by customers and load aggregators at the retail or wholesale level (Cappers 2009).

In addition, Title XIII of the 2007 Energy Independence and Security Act sets U.S. policy for the “Development and incorporation of demand response, demand-side resources, and energy-efficiency resources” and to “develop advanced techniques for measuring peak load reductions and energy-efficiency savings from smart metering, demand response, distributed generation, and electricity storage systems.”

The 2009 American Recovery and Reinvestment Act provided the U.S. Department of Energy (DOE) with the economic resources for the implementation of Title XIII of the 2007 Energy Independence and Security Act. The main two initiatives funded by the Recovery Act are the Smart Grid Investment Grant (SGIG) and the Smart Grid Demonstration Program (SGDP). SGIG supports the deployment of existing smart grip technologies, while SGDP focuses on the development of smart grip and energy storage systems.

An important component of the SGIG is the funding of consumer behavior studies that assess its impact on a variety of variables including peak demand and consumer acceptance and retention. Section 2.3 of this study reviews five of these pilot programs.

Current Status of Demand Response

The potential peak load reduction from DR at the national level was estimated at about 5.0% in 2006 and grew to 5.8% in 2008. In that same year, 38,000 MW of potential peak load reductions were available for provision by customers enrolled in incentive-based DR programs, while about 2,700 MW were available from customers enrolled in Time-Based DR programs (Cappers 2009). FERC estimated total potential peak load reduction at about 66,351 MW in 2012 of which about 8,134 MW was associated with residential customers (see Figure 2.1).

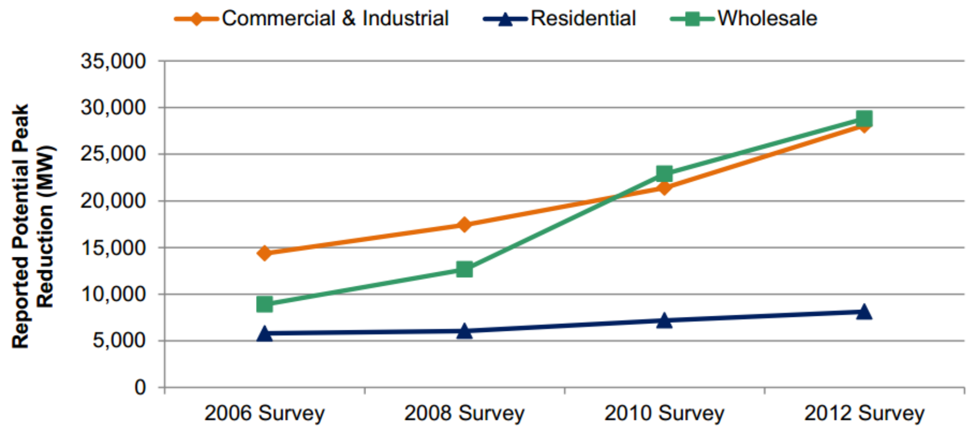

Figure **2-1**: Reported potential peak reduction by customer class in 2006, 2008, 2010, and 2012 (FERC 2012).

About 50.4 percent of households in the United States have smart meters, but only one percent of those households are under time-varying tariffs and one percent of that one percent under dynamic pricing (See Figure 2.2). It is estimated that the current DR potential ranges from three to nine percent of a region's summer peak demand in most regions of the United States (FERC 2012, Faruqui et al. 2014).

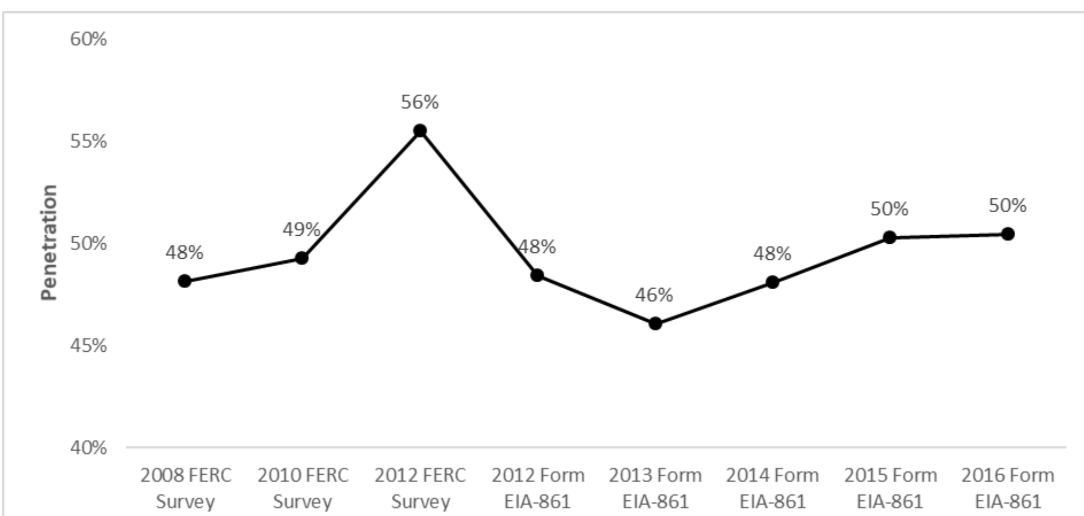

Figure **2-2**: Estimated advanced metering penetration nationwide reported in FERC Surveys 2008 to 2012 and EIA Forms 2012 to 2016 (FERC 2018).

Although several studies have reported aggregated reductions on peak consumption achieved by economic DR programs, the same studies have found variability in participants' responses to dynamic rates at the individual level. This is expected to change (positively or negatively) as customers become more familiar with these programs. As customers become more educated about the benefits of Economic-Based DR programs demand could not only become more elastic to changes on electricity prices, but also customer responses could be more persistent. The opposite could also be true, and as customers get more used to dynamic tariffs and enabling technologies, they could just ignore them (Faruqui, Sergici and Sharif 2009). The answer to this empirical question will only arrive as data from multi-year pilot studies becomes available. In the hypothetical case that demand in fact becomes more elastic and persistent in their responses, utilities will be able to predict the level of customer response over a range of different prices, opening the door to more participation of DR resources in wholesale electricity markets. If the opposite holds, Economic-Based demand response programs should not be pursued, and instead, other alternatives like Incentive-Based DR programs and distributed generation should continue to be expanded.

The expansion of Incentive-Based programs has already taken place. According to FERC's 2018 Assessment of Demand Response and Advance Metering, these demand response programs represented the bulk of potential peak load reduction, with Interruptible Load, Direct Load Control and Load as a Capacity Resource making up to 68 percent of the reported potential peak reduction in 2018. In their 2018 Long-Term Reliability Assessment, NERC reports that total potential peak demand savings from retail demand response programs increased by almost 3,050 megawatts (MW), or approximately nine percent, between 2015 and 2016, to 35,924 MW. this type of DR program will continue experiencing a significant growth in the next decade and is projected to reach 50,000 MW by 2021. This represents approximately 9 percent of the on-peak resource portfolio and will be able to offset approximately four years of peak demand growth. On the other hand, programs that offered dynamic rates were estimated to represent less than 1 percent of total peak load reductions with CPP representing the highest potential for residential customers. Time-of-Use programs, which are a non-dynamic Time-Based type of DR program, made up 12 percent of all reported demand response potential peak reduction, and after Direct Load Control that was the main source of DR from residential customers.

Literature Review

In spite of the numerous estimates of the potential peak load reductions associated with different DR programs, several challenges still remain for a higher penetration and a more accurate quantification of the benefits attributed to Demand Response. So far, utilities in charge of the different pilots carried out across the country have used different experimental designs and methodological approaches to measure and verify demand reductions. This divergence in methodologies and designs reduces the comparability of the obtained results. Additionally, the lack of protocols for communicating demand response pricing, signals, and usage information also constitute barriers for the evaluation process of DR programs. Finally, FERC has also highlighted the need to make further efforts directed at developing more DR forecasting and estimation tools.

Before presenting a summary of the most recent DR pilot programs, I review some of the studies involving dynamic pricing in order to show the different methodological trends.

Herter et al. (2005) summarizes the results of a dynamic pricing study in California. The experiment features a Critical Peak Pricing rate (CPP) and provided some customers with Programmable Communicating Thermostats (PCTs). The study found that, on average, customers without the enabling technology reduced their consumption during critical peak periods by about 13%. While customers with the enabling technology were reported to reduce electricity use as much as 25% and 41% for 5-hour and 2-hour critical events respectively. Herter (2007) presents an evaluation of the 2003-2004 California Statewide Pricing Pilot. The author found evidence showing that high-use customers on CPP tariffs respond significantly more than low-use customers. Similarly, the study found that low-use customers save more in percentage reductions on their electricity bills than high-use customers do. The study reveals statistically indistinguishable load and bill changes across income levels. Earle and Faruqui (2006) analyze the value provided by demand response programs and highlight the need for developing an approach that allows an accurate quantification of this value. Among other things, the authors recommend the adoption of the Kaldor-Hicks Optimality concept instead of the more restrictive Pareto Optimality when evaluating demand response programs.

Faruqui and George (2006) provide a series of conditions to take into consideration when designing dynamic tariffs. They emphasize that prices must convey information on resource scarcity, and they highly rate design criteria like simplicity, equity and revenue recovery, and stability. Wolak (2006) applied a non-parametric conditional mean analysis to a dataset of customers under a CPP tariff offered by the City of Anaheim Public Utilities (APU) from June 2005 to October 2005. The author found average reductions of 12 percent during peak hours. Albadi and El-Saadany (2008) present a description of the reasoning behind Demand Response programs, as well as a description of the different types of DR programs and the benefits and costs associated to dynamic tariffs. Walawalkar et al. (2008) performed a welfare analysis of the economic demand response in place in the PJM market using load and price data from 2006. They found that although wealth transfers from generators to non-price responsive loads exceeded those given to responsive loads, the overall social welfare gains exceed the distortions introduced by the incentive payments.

Using empirical evidence provided by FERC’s Assessment of Demand Response and Advance Metering, Cappers et al. (2009) summarize the evolution of DR programs in U.S. electric power markets. They report a significant increase in the amount of DR available in the country, and highlight the fact that although Time-Based DR programs represent a small share of potential peak load reductions, they are the ones more commonly available to end-users. Faruqui, Hledik and Tsoukalis (2009) use the Pricing Impact Simulation Model (PRISM) and consumption data from a California utility to simulate the impact of dynamic tariffs on system peak load. They estimated potential peak reductions between 1 and 9 percent with associated benefits for the estate of California of $0.6 to $6 billion. Faruqui, Hledik and Sergici (2009) give a detailed description of how pilot DR projects should be designed and evaluated. Sample and experimental design criteria are provided. Additionally, a review of several Dynamic Pricing Pilots is included. Reductions in peak load consumption of as much as 13 percent were reported for the five pilot studies featuring CPP, TOU, PTR, RTP, and enabling technologies.

Faruqui, Sergici and Sharif (2009) review twelve pilot programs in the United States that involve the use of In-Home Displays (IHDs). They found that customers that actively use the information provided by IHDs can reduce their electricity consumption by as much as 13 percent. The paper also reports that when Time-of-Use tariffs are complemented with IHDs customers' response to price changes increases. Faruqui and Sergici (2010) performed a review of fifteen DR pilots in the U.S. They found evidence of customer responsiveness to price signals. However, they also found that the magnitude of the responses depends on several factors including: the rate of the price increase, the availability of enabling technologies, and the ownership of central air conditioning. All the studies found that TOU tariffs produce a drop in peak demand ranging from 3 to 6 percent. CPP tariffs produce a reduction in peak load that ranges from 13 to 20 percent. Finally, it was found that when complemented with enabling technologies, CPP tariffs produce reductions in the 27-44 percent range.

Faruqui and Sergici (2011) evaluate the dynamic pricing pilot carried out by The Baltimore Gas and Electric Company (BGE) during the summers of 2008 and 2009. Using a constant elasticity of substitution (CES) model on customers enrolled in CPP and PTR tariffs, they found reductions in peak usage in the range of 18 to 33 % for the summer of 2008, and found no significant differences in the reductions for the summer of 2009. Faruqui et al. (2012) presents evidence of responsiveness to dynamic pricing in moderate climates. They analyzed data from a pilot DR project carried out in Connecticut that featured a Time-of-Use rate, two dynamic pricing rates, and four enabling technologies. Using a constant elasticity of substitution model (CES), they found evidence of customers' response to dynamic pricing and also found that these responses are boosted by enabling technologies.

Summary of pilot studies

This section reviews five DR pilot studies that have taken place in the U.S. in the past decade. The studies reviewed cover different dynamic tariffs and some of them incorporate different enabling technologies. These studies are a part of the eleven Consumer Behavior Studies (CBS) funded by the U.S. Department of Energy (DOE) under the Smart Grid Investment Grant (SGIG). I provide a comparison of the results obtained from these pilots and discuss their implications. It is worth noting that due to the different experimental designs, populations, and geographic locations, the results of the different studies are not directly comparable. However, the magnitude of the changes in consumption patterns produced by the programs is indicative of their effectiveness. The pilots reviewed in this section are listed in Table 2.1 while results from the individual pilots are summarized in Table 2.18.

My review suggests that consumers respond to price signals. The studies reported reductions ranging from 5.7% to 41.8% on peak consumption. Enabling technologies were reported to significantly enhance customers' responses in two of the reviewed studies while in the other three these technologies were reported to play a marginal role. The reviewed reports lack information regarding the persistence of customers' responses to time-varying prices. This aspect is crucial to estimate the usefulness of Price-Based demand response as a tool for system planning and reliability.

Table **2-1**: Reviewed pilot studies.

No.	**Pilot**	**State**	**Utility**	**Year**
1	Smart Study TOGETHER	Oklahoma	Oklahoma Gas and Electric (OG&E)	2010-2011
2	Consumer Behavior Study	Massachusetts	Marblehead Municipal Light Department (MMLD)	2011-2012
3	Smart Sacramento Project	California	Sacramento Municipal Utility District (SMUD)	2012-2013
4	Smart Currents Home Project	Michigan	Detroit Edison Company (DECo)	2012-2013
5	SGIG Consumer Behavior Study	Minnesota	Minnesota Power (MN Power)	2012-2014

Oklahoma Gas and Electric

Oklahoma Gas and Electric (OG&E) offered a residential TOU/CPP pilot program with enabling technologies. The pilot program featured two rate designs: A traditional TOU with CPP tariff and a Variable Peak Price (VPP) with a CPP overlay. Under the TOU/CPP tariff customers faced a five-hour peak period (2-7 p.m.) during the summer season (June to September) and were notified of critical peak events at least two hours in advance at any time of the year when a reduction in load was required. The VPP/CPP tariff also utilized a five-hour peak period and a CPP component applicable any time of the year, but it differed from the traditional TOU/CPP program in that the price applicable during the daily five-hour peak period was picked by OG&E from a set of four pre-determined levels on a day-ahead basis.

Table **2-2**: OG&E rate levels (¢/kWh).

Period	TOU w/ CPP	VPP w/ CPP
Off-peak	4.2	4.5
Low Peak	23.0	4.5
Standard Peak	23.0	11.3
Medium Peak	23.0	23.0
High Peak	23.0	46.0
Critical Event	46.0	46.0

The design of the experiment was a Randomized Controlled Trial (RCT) that included eight treatment groups and one control group on an opt-in basis. The pilot was implemented in two phases with two different subsets of customers in each phase. Phase I took place in 2010 and Phase II took place in 2011.

All customers participating in the program had access to a web portal with information on tariffs and consumption, but some also were given In-Home Displays (IHDs) or Programmable Communicating Thermostats (PCTs). The final treatment group was equipped with IHDs and PCTs, as well as access to a web portal.

Table **2-3**: OG&E sample size and enable technologies.

	Control	**TOU w/ CPP**	**VPP w/ CPP**	**Total**
Control	549	-		549
Web	-	282	276	558
IHD	-	249	249	498
PCT	-	218	213	431
All Three	-	246	234	480
Total	**549**	**995**	**972**	**2516**

Results

During the period of study all customers reduced consumption during the Peak periods. However, customers with IHDs showed more consistent responses throughout the peak period. Results are shown in Table 2.4.

Table **2-4**: OG&E Average Customer Consumption and Savings.

	On-Peak Consumption (kW)			Off-Peak Consumption (kW)			Overall
	Baseline	Change	Percent	Baseline	Change	Percent	Change
TOU w/ CPP							
Web Only	10.80	-2.14	-19.80%	25.20	0.97	3.86%	-1.17
IHD Only	10.80	-2.76	-25.58%	25.20	0.40	1.57%	-2.37
PCT Only	10.85	-4.21	-38.80%	25.16	3.16	12.58%	-1.05
All Three	10.80	-3.31	-30.60%	25.20	1.44	5.71%	-1.87
VPP w/ CPP							
Web Only	10.80	-1.57	-14.52%	25.20	0.52	2.08%	-1.04
IHD Only	10.80	-1.45	-13.40%	25.20	-0.20	-0.79%	-1.65
PCT Only	10.85	-3.49	-32.15%	25.16	3.59	14.28%	0.10
All Three	10.80	-3.32	-30.78%	25.20	2.26	8.95%	-1.07

Reference

https://www.smartgrid.gov/sites/default/files/doc/files/GEP%20OGE%20Summer%202010%20Report%20Final-copyright%20corrected.pdf

Marblehead Municipal Light Department

Marblehead Municipal Light Department (MMLD) offered a residential Flat with a CPP pilot program and enabling technologies. The pilot program featured a CPP tariff under which customers faced a six-hour peak period (12-6 p.m.) from June through August. Customers were notified of critical peak events on a day-ahead basis.

Table **2-5**: MMLD rate levels (¢ per kWh).

Period	Standard Rate	Flat w/ CPP
Basic Monthly Charge	425	425
Off-peak	14.25	9.0
Critical Event	14.25	105.0

The design of the experiment was a Randomized Controlled Trial (RCT) that included one treatment group and one control group on an opt-in basis. All customers participating in the program had access to a web portal with information on tariffs and consumption. In addition to this, in year two of the study all participating customers were offered a free water heater (WH) or PCT.

Table **2-6**: MMLD sample size and enabling technologies.

	Control	Flat w/ CPP	Total
Control	223	-	223
Web	223	264	518
WH	6	7	13
PCT	25	20	45

Results

Reported results show that customers under the CPP rate achieved significant reductions in peak demand with respect to customers in the control group. In the first year, the average kW reduction from CPP customers during the three event days was 0.74 kW, a reduction of 36.7%. For year two this figure was 0.37 kW, a reduction of 21.3%. The lower impact in year two relative to year one can be attributed to a lower average daily temperature (87.3°F in 2011 versus 83.7°F in 2012). Results are shown in Table 2.7.

Table **2-7**: MMLD Average Customer Consumption Impacts.

Impact Metric	Value	Units	Description
Year One (2011)			
Average Hourly Impact on Electricity Consumption Over All Events	-36.7%	%Change	Over critical events in CPP Program
	(186.72)	kW	
Year Two (2012)			
Average Hourly Impact on Electricity Consumption Over All Events	-21.3%	%Change	Over critical events in CPP Program
	(194.04)	kW	

Reference

https://www.smartgrid.gov/sites/default/files/Marblehead%20Final%20Evaluation%20Report%20with%20Appendices%202013-07-01-1_0.pdf

Sacramento Municipal Utility District

Sacramento Municipal Utility District (SMUD) offered a residential TOU/CPP pilot program with enabling technologies. The pilot program featured three rate designs: A traditional TOU, a TOU tariff with a CPP overlay, and a Flat tariff with a CPP overlay. Under the TOU tariff, customers faced a three-hour peak period (4-7 p.m.). Customers participating in the TOU with CPP and Flat with CPP tariffs were notified of critical peak events on a day-ahead basis when high prices or system contingencies were expected.

Table **2-8**: SMUD rate levels (¢ per kWh).

Period	TOU	TOU w/ CPP	Flat w/ CPP
Base (<700 kWh)	-	-	8.5
Base (>700 kWh)	-	-	16.7
Off-Peak (<700 kWh)	8.5	7.2	-
Off-Peak (>700 kWh)	16.6	14.1	-
Peak	27.0	27.0	-
Critical Event	-	75.0	75.0

The pilot included three different experimental designs: Randomized Controlled Trial (RCT), Randomized Encouragement Design (RED), and Within-Subject Design. Seven treatment groups and one control group were included, four of them on an opt-in basis and three on an opt-out basis. Each tariff included a subset of customers that were equipped with IHDs.

Table **2-9**: SMUD sample size and enabling technologies.

Recruitment Approach		IHD Offer	# of Customers
Opt-in	CPP	No	223
		Yes	1651
	TOU	No	1229
		Yes	2199
Default	CPP	Yes	701
	TOU	Yes	2018
	TOU w/ CPP	Yes	588

Results

For customers under the TOU tariff, the largest average cross year reductions on peak consumption were reported for those enrolled in the opt-in TOU group that was offered an IHD. Average impact for this treatment group was 11.9% of the whole house reference load. However, after correcting for pre-treatment differences across treatment groups, the load impact differences were not statistically significant. Hence, there is no evidence indicating that IHDs significantly increase load impacts associated with time varying rates. Table 2.10 shows the impact of all TOU tariffs on customers.

Table **2-10**: SMUD Load Impacts for TOU Pricing Plans.

Group	Year	Average Impact per Customer (kW)	Reference Load (kW)	Impact as % of Reference Load
Opt-in TOU, No IHD Offer	2012	0.17	1.71	10.0%
	2013	0.15	1.69	9.1%
	Average	0.16	1.72	9.4%
Opt-in TOU, IHD Offer	2012	0.24	1.80	13.1%
	2013	0.20	1.79	10.9%
	Average	0.21	1.79	11.9%
Default TOU, IHD Offer	2012	0.12	1.87	6.2%
	2013	0.10	1.80	5.7%
	Average	0.11	1.86	5.8%
Default TOU with CPP, IHD Offer	2012	0.16	1.90	8.2%
	2013	0.18	1.85	9.6%
	Average	0.17	1.91	8.7%

Reported average load reductions for the opt-in CPP plan with IHD offer was roughly 25.1% of the whole household load. This figure was approximately 20.9% for the opt-in CPP plan with no IHD offer. Results for all customers under the CPP rate are shown in Table 2.11.

Table **2-11**: SMUD Load Impacts for CPP Pricing Plans.

Group	Year	Average Impact per Customer (kW)	Reference Load (kW)	Impact as % of Reference Load
Opt-in CPP, No IHD Offer	2012	0.52	2.38	21.9%
	2013	0.46	2.25	20.6%
	Average	0.49	2.33	20.9%
Opt-in CPP, IHD Offer	2012	0.69	2.62	26.2%
	2013	0.60	2.48	24.1%
	Average	0.64	2.53	25.1%
Default CPP, IHD Offer	2012	0.32	2.64	12.1%
	2013	0.41	2.47	16.5%
	Average	0.36	2.56	14.0%
Default TOU w/ CPP, IHD Offer	2012	0.33	2.61	12.8%
	2013	0.29	2.43	11.9%
	Average	0.24	2.54	12.3%

Reference

https://www.smartgrid.gov/sites/default/files/doc/files/SMUD_SmartPricingOptionPilotEvaluationFinalCombo11_5_2014.pdf

Detroit Edison Company

Detroit Edison Company (DECo) offered a residential TOU with CPP pilot program with enabling technologies. The pilot program featured a three-period TOU rate with a CPP overlay. Participating customers faced two shoulder periods (7a.m. to 3 p.m. & 7 p.m. to 11 p.m.) and a peak period (3-7 p.m.). Customers were notified of critical peak events on a day-ahead basis.

Table **2-12**: DECo rate levels (¢ per kWh).

Period	TOU w/ CPP
Off-peak	4.0
Shoulder	7.0
Peak	12.0
Critical Event	100.0

The design of the experiment was a Randomized Controlled Trial (RCT) that included one treatment group and one control group on an opt-in basis.

Participating customers who self-identify as having central air conditioning were randomly assigned to a control or TOU with CPP treatment group that included an offer to receive an IHD, a PCT or no technology. On the other hand, participating customers who self-identify as not having central air conditioning were randomly assigned to a control or TOU with CPP treatment group that included an offer to receive an IHD or no technology.

Table **2-13**: DECo sample size and enable technologies.

	Control	TOU w/ CPP	Total
Control	1212	-	1212
No Technology	-	249	249
IHD	-	390	390
PCT	-	328	328
IHD+PCT	-	369	369

Results

According to reported results during event days, customers in the no-technology treatment group reduced their peak hour loads by 12.6% compared to the control group. On the other hand, customers with IHDs reduced their consumption during peak hours by roughly

17.5%. The largest load reductions during critical peak hours were reported for customers with PCTs and PCTs+IHDs, with reductions at 44.5% and 43.0% respectively. The results are shown in the table below.

Table **2-14**: DECo Average Load Impacts by Usage Type and Enabling Technology.

Usage Type	Technology	Peak period consumption (kWh)			Total consumption (kWh)		
		Control	Impact	Impact%	Control	Impact	Impact%
Medium Usage	No Technology	7.751	-1.378	-17.78%	33.811	-0.992	-2.93%
	With IHD	7.751	-2.084	-26.89%	33.811	-0.380	-1.12%
	With PCT	9.401	-4.025	-42.81%	37.923	-3.278	-8.64%
	With IHD and PCT	9.401	-3.709	-39.45%	37.923	-3.233	-8.53%
High Usage	No Technology	15.629	-1.741	-11.14%	67.933	2.654	3.91%
	With IHD	15.629	-2.987	-19.12%	67.933	2.597	3.82%
	With PCT	16.680	-6.725	-40.32%	69.231	-8.947	-12.92%
	With IHD and PCT	16.680	-6.983	-41.86%	69.231	-7.346	-10.61%

Reference

https://www.smartgrid.gov/sites/default/files/doc/files/DTE-SmartCurrents_FINAL_Report_08152014.pdf

Minnesota Power

Minnesota Power (MN Power) offered a residential TOU/CPP pilot program with enabling technologies. The pilot program featured a TOU rate with a CPP overlay. Under the TOU/CPP tariff customers faced a fourteen-hour peak period (8a.m.-10p.m.) with higher prices when declared critical peak events took place. These events were declared when there was a high probability of the system facing unusual load levels or any other contingency.

Table **2-15**: MN rate levels (¢ per kWh).

Period	TOU w/ CPP*
Off-peak	-2.990
Peak	1.415
Critical Event	77.000

*The presented values are adders to an existing increasing block rate.

The design of the experiment was a Randomized Controlled Trial (RCT) that included eight treatment groups and one control group on an opt-in basis.

All customers participating in the program had access to a web portal with information on tariffs and consumption. The granularity of the feedback provided by the utility changed across treatment groups. Some customers received hourly feedback on a daily basis, others received daily information on a daily basis and a final group received monthly feedback on a monthly basis.

Table **2-16**: MN sample size.

	Voluntary participants	Assigned Participants
Monthly feedback (Control)	768	494
Daily feedback	767	494
Hourly feedback	768	494

Results

No statistically significant electricity savings were reported for either of the treatment groups. The results are shown in the table below.

Table **2-17**: MN Average Load Impacts by Treatment Group.

		Avg. pre-pilot usage	Avg. change in usage		Avg. net change in usage (treatment-control)		n
Pool	Group	annual kWh	kWh	%	kWh	**%**	
Voluntary	Hourly	9,491	172	3.3%	-51	-0.5%	454
	Daily	9,950	254	4.0%	330	0.3%	464
	Monthly (Control)	9,666	224	3.7%			457
Assigned	Hourly	8,375	176	3.9%	-36	-0.4%	672
	Daily	8,285	340	7.9%	129	1.6%	693
	Monthly (Control)	8,220	211	4.7%			681

Reference

https://www.smartgrid.gov/sites/default/files/MN%20Power%20CBP%20Interim%20Report.pdf

Summary Results

My review indicates that customers do respond to price signals. Evidence of significant reductions on peak load is observed in four of the five reviewed studies. The studies reported reductions ranging from 5.7% to 41.8% on peak consumption. In two of the studies, enabling technologies were reported to significantly enhance customer response, while in the other three these technologies played a marginal role. Results are summarized in Table 2.18. The reviewed reports lack information regarding the persistence of customers' responses to time varying prices. This aspect is crucial to estimate the usefulness of Price-Based demand response as a tool for system planning and reliability.

Table **2-18**: Summary of the results of the reviewed studies.

	Pilot	Utility	Tariffs				Enabling Tech			Enrollment		Impact Range (Peak Period)
			Flat	TOU	VPP	CPP	IHD	PCT	WH	Opt-In	Opt-Out	
1	Smart Study TOGETHER	OG&E		*	*	*	*			*		(-13.4%, -38.8%)
2	Consumer Behavior Study	MMLD	*			*		*	*	*		(-21.3%, -36.7%)
3	Smart Sacramento Project	SMUD	*	*		*	*			*	*	(-5.7%,-13.1%)
4	Smart Currents Home Project	DECo		*		*	*	*		*		(-11.14%,-41.86%)
5	SGIG Consumer Behavior Study	MN Power		*		*				*	*	-

Chapter 3

Impact Analysis of the GMP Consumer Behavior Program

Introduction

When electricity demand is at or near its highest level, more expensive and less efficient generators have to be dispatched by the system operator in order to meet the additional peak demand. The utilization of these units result in higher generation cost that translates into higher wholesale electricity prices. Time-varying tariffs are being tested by different utilities as tools to incentivize reductions in electricity consumption during hours of high demand. Different studies have reported that customers do respond to price signals (Faruqui et al. 2014, Herter et al. 2007). However, some studies have also reported that responses are not persistent across events with similar dynamic prices and weather conditions (Faruqui et al. 2009, Faruqui et al. 2012). This creates the need for further research on the topic of time-varying prices. Using data from a pilot study carried out by Green Mountain Power (GMP) as a component of the eEnergy Vermont Smart Grid project in Rutland, VT I seek to provide evidence of changes in electricity demand due to price signals. In order to achieve this objective, I implement a difference-in-differences model to a dataset of 16,545 households randomly divided into 8 groups, each of which was assigned a different pricing treatment during declared peak hours.

The pilot study ran from March 2012 through September 2013. During the fall of 2012 and summer of 2013, GMP called fourteen critical peak event days (see Table 3.2). Participating customers were notified of events on a day-ahead basis. Critical peak events began at 1p.m. and ended at 6p.m. Temperatures during peak events were between (68-77°F) in 2012 and (69-90°F) in 2013. Higher levels of demand were observed during 2013 events.

At the aggregate level I found evidence of reductions in electricity consumption during critical peak events, with customers under the Critical Peak with In-Home Display tariff (CPP-I) showing the highest response. On average, these households reduced electricity demand by 0.075kW/h during critical events with respect to the control group. Similarly, on average, customers under the Critical Peak tariff reduced electricity demand by 0.067kW/h. In the case of the Critical Peak Rebate (CPR) and Critical Peak Rebate with In-Home Display (CPR-I) groups, the aggregate impact of the interventions was of the same magnitude; around 0.042kW/h and 0.044 kW/h respectively.

At the event-specific level, except for the first critical event in 2012, the pricing structures associated with the CPR and the CPR-I treatments does not seem to be effectively reducing consumption of electricity during peak hours. A similar conclusion could be stated for the CTRL-N treatment. Unlike the latter treatments, CPP and CPP-I treatments seem to be effective. However, the magnitude of the effect does not appear to be persistent over time. The rest of this chapter is organized as follows: section 3.2 presents the market research, section 3.3 details the experimental design of the pilot, section 3.4 describes the data and methodology, section 3.5 presents an unconditional analysis of mean electricity consumption for the treatment and control groups, section 3.6 describes the econometric model implemented for estimating the conditional impact of electricity rates on electricity consumption, section 3.6 presents results and section 3.7 concludes.

Market Research

Green Mountain Power (GMP) is an investor-owned electric utility and an indirect subsidiary of Canada's Énergir that serves about 80 percent of Vermont's customers (265,000 households). In 2013 peak summer and winter demands for the GMP system were 734 MW and 737 MW respectively (EIA 2013).

Rutland County, like the state of Vermont, is classified as climate zone 6 (see Figure 3.1) with an all-time record high temperature of 102°F registered in July 2008 and an all-time low temperature of -43°F registered in January 1994 (International Energy Conservation Code, 2013).

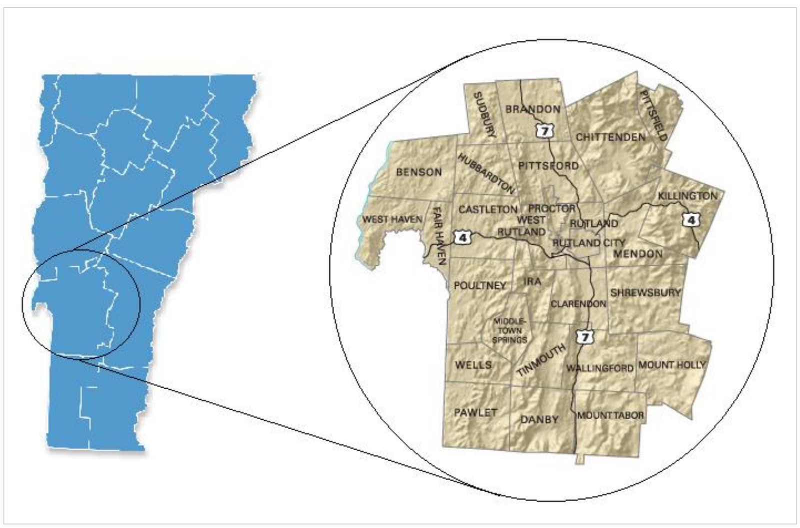

Figure **3-1**: Rutland County and Vermont climate zones.

Target Population

As of 2014, Rutland had a population of 60,086. Estimated median household income in 2013 was $49,271 compared to an average of $54,267 for the state of Vermont. The most important industries in the county are manufacturing, retail trade, and construction (U.S. Census Bureau).

Experimental Design

Rate Design

Green Mountain Power (GMP) offered a residential Flat with a CPP or CPR pilot program with enabling technologies. The pilot program featured two rate designs: A Flat rate with CPP tariff and a Flat rate with a CPR overlay. Under the Flat with CPP tariff, customers faced a five-hour peak period (1p.m-6p.m) during declared critical peak events that could be called during any time of the year with a day-ahead notification. Customers participating in the Flat with CPP program faced lower electricity prices than they would have faced under the flat rate during non-critical events, and higher than usual prices during declared peak events. Similarly, customers enrolled in the Flat with CPR rate faced a five-hour peak period (1p.m- 6 p.m.) during declared peak events, but instead of paying higher electricity prices for consumption during this period, customers received payments for reducing their consumption (relative to a measured baseline) during peak events, and paid the existing flat rate during non-peak events.

Table **3-1**: GMP rate levels (¢/kWh).

Period	Flat Rate	Flat with CPP	Flat with CPR
Base	14.8	14.4	14.8
Critical Event	14.8	60.0	14.8-(60.0 reduction from baseline)

The experiment design was a randomized controlled trial (RCT) that included six treatment groups and two control groups. Once enrolled, customers assigned to the Flat with CPP treatment group could not opt-out of the rate, while customers in any other treatment group could opt-out if they choose to. Among the treatment groups, there was one group of customers that were transitioned from the Flat with CPR rate in year one of the study (2012) to the Flat with CPP rate in year two (2013). All customers participating in the program had access to a web portal with information on interval meter data and educational material. Additionally, each rate design included a treatment group that received In-Home Displays (IHDs) and another that did not. The characteristics of each group were as follows:

1. **Critical Peak Price (CPP):** During declared peak hours electricity prices raised to $0.60 per kWh, a substantial increase relative to the customer's default rate.
2. **Critical Peak Price + IHD (CPP-I):** In addition to the same rate treatment as the CPP group, this group received an In-Home Display which enabled them to get information on real-time energy usage.
3. **Critical Peak Rebate (CPR):** During declared peak hours customers received a rebate of $0.60 per kWh for energy reductions (relative to a measured baseline).
4. **Critical Peak Rebate + IHD (CPR-I):** In addition to the same rate treatment as the CPR group customers, this group received IHDs.
5. **Critical Peak Rebate during the first year and Critical Peak Price during the second year (CPR-CPP)**: During the first year, customers were placed on CPR and then recruited to move to CPP for the second year.
6. **Critical Peak Rebate during the first year and Critical Peak Price during the second year + IHD (CPR-CPP-I):** This group was treated the same as the previous one but customers received IHDs.

7. **Flat Rate + Notification (CTRL-N):** This group remained on the default rate but was notified of peak-time events.
8. **Control Group (CTRL):** This group remained on the default rate but was not notified of peak-time events.

The inclusion of groups 5 and 6 in the original project had the purpose of evaluating whether customer acceptance of CPP could be increased if customers were first placed on CPR and then asked to move to CPP. This chapter will not focus on this potential effect, so customers on CPR-CPP and CPR-CPP-I will be treated as CPR and CPR-I during the first year and CPP and CPP-I during the second year respectively. This approach does not present any potential problems for customers on CPR-CPP or CPR-CPP-I because at the beginning of the project they did not know that they would be asked to move to a different treatment. Therefore, this study has six relevant groups, and its main objective is to estimate the causal impact of the different treatments on electricity consumption.

Event Days

The pilot ran from March 2012 through September 2013. During the fall of 2012 and summer of 2013, GMP called fourteen critical peak event days (see Table 3.2). Participating customers were notified of events on a day-ahead basis. Critical peak events began at 1p.m. and ended at 6p.m.

Table **3-2**: Average temperatures and heat index during critical peak days.

Event Date	Ave. Temperature (°F)	Ave. Heat Index (°F)
9/14/2012	77.8	75.7
9/21/2012	69.2	66.9
9/25/2012	65.4	62.6
10/5/2012	70.4	68.2
7/5/2013	86.4	83.5
7/15/2013	87.8	84.7
7/16/2013	86.4	83.6
7/17/2013	89.0	85.7
7/18/2013	87.0	84.1
7/19/2013	90.0	86.6
8/13/2013	68.4	66.2
8/21/2013	82.2	79.8
8/22/2013	82.0	79.6
8/28/2013	82.4	80.0

Sample Design

According to information from GMP, 16,545 eligible customers in the vicinity of Rutland, VT were randomly assigned to one of the 8 groups mentioned above. After being contacted by phone or e-mail, each customer could decide to participate or not. Consequently, the encouragement to take the treatment rather than the treatment itself was randomly assigned to customers. This design is called Randomized Encouragement Design (RED). For example, out of a total of 2,884 customers randomly assigned to participate in the CPR group, 393 were initially recruited. It is reasonable to assume that those who accepted the new rate are in some way different from those who declined the phone survey or did not respond the e-mail invitation. Therefore, a direct comparison between those treated and the control group would be biased.

Traditionally this sort of self-selection problem is solved by using randomly assigned treatment as an instrumental variable for treatment received. Under reasonable assumptions, this strategy estimates the Local Average Treatment Effect or LATE parameter (Angrist, Imbens and Rubin, 1996). The LATE parameter is the average effect of treatment on those individuals who change their behavior due to the instrument. Furthermore, in this study no one in the control group had access to the experimental intervention, which means that the LATE parameter was the only variable influencing change.

In this case, the sample includes information from customers that accepted their treatment and remained on it and also from customers that decided to stop participating after being placed on their treatment status. In particular, the available information corresponds to the 2,565 customers who were recruited or enrolled in the study in March 2012 (afterwards, some customers decided to drop-out of the study but their information is available in the database). However, it does not contain information from all the customers who decided to opt-out after being randomly encouraged to participate. In other words, the data on the 16,545 customers randomly assigned to one of the treatment groups is not available. Therefore, an instrumental variable approach cannot be implemented in order to estimate the LATE parameter.

This study will use a difference-in-differences approach to examine whether those treated effectively reduced their electricity consumption. In particular, the impact of the program intervention will be measured by the difference in the variation of energy loads between non-peak hours and peak hours between treated and non-treated customers.

Data and Methodology

Data

The dataset covers the period from March 2012 to September 2013. It contains 28,181,268 hourly observations on the energy load from customers. As reported by GMP, customers in the CPR and CPP groups were transitioned to their new rate structures in August 2012, and IHDs were mailed to the respective customers during the second two weeks of August 2012. Also, customers in the CPR-CPP and CPR-CPP-I groups who decided to continue participating in the program were transitioned to their new rate during May 2013. Consequently, the main analysis in this study will be focused on two periods: from August 2012 to December 2012 and from May 2013 to September 2013. In this way, potential problems arising from the inclusion of participants not yet on their correct treatment will be avoided. Further, given the shortage of information on customers who declined to participate in the program, the analysis and estimations will be carried out with the data on those customers who accepted their treatment and those who, after being placed on their treatment, decided to opt-out.

The distribution of customers across groups and over time for the years 2012 and 2013 is shown in Tables 3.3 and 3.4. It is important to note that for both years the reduction in the number of customers in each group was caused by traditional sample attrition or by the fact that some customers eventually decided to opt-out of treatment but remained into the sample. Even though each type of process could eventually respond to different causes, they will be considered equal to each other.

Table **3-3**: Distribution of customers across groups (2012).

Group and Status	Month										Attrition Rate*
	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	
CPR	393	393	363	363	362	362	356	355	352	350	11%
CPR-I	204	204	204	204	203	203	188	188	187	187	8%
CPP	392	392	390	390	388	387	329	320	320	320	18%
CPP-I	195	195	195	195	195	195	158	154	153	153	21%
CPR-CPP	391	391	391	391	391	391	353	351	343	321	22%
CPR-CPP-I	195	195	195	195	195	195	172	172	172	172	4%
CTRL	398	397	396	394	392	386	388	386	383	382	4%
CTRL-N	397	397	393	393	393	393	384	383	383	383	8%
Total	2565	2564	2527	2525	2519	2512	2328	2309	2293	2268	12%

Only customers that accepted their treatment and remained on it and customers that decided to stop participating after being placed on their treatment status.
*Calculated from March to December 2012.

As it can be seen from Table 3.3 during 2012 the CPR-CPP group had the highest attrition rate, followed by the CPP-I and CPP groups. During 2013 the attrition is higher and it is specially concentrated in the CPR-CPP and CPR-CPP-I groups. With regard to the impact analysis, it is necessary to know if the attrition correlates with the treatments being evaluated this because a random attrition will only reduce the statistical power of the study. At first glance, the fact that attrition rates are not similar in treatments and control groups might imply that the decision to opt-out is correlated with the treatment received. Still, it is not possible to assure that the attrition is not random. The proper analysis consists of comparing customers who dropped-out with customers that remained using baseline data to see if they differ systematically, at least in observable dimensions. Given that the project did not include a baseline survey, this analysis cannot be performed. Descriptive statistics are shown in Table 3.5.

Table **3-4**: Distribution of customers across groups (2013).

	Month									
Group and Status	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	**Attrition Rate***
CPR	327	325	323	322	322	321	314	314	309	6%
CPR-I	180	174	174	174	174	173	170	167	167	7%
CPP	318	313	310	306	299	299	299	280	270	15%
CPP-I	153	141	140	139	139	139	134	134	132	14%
CPR-CPP	311	228	225	219	217	217	217	216	191	39%
CPR-CPP-I	162	135	125	117	112	105	105	105	104	36%
CTRL	383	383	383	381	376	369	369	369	368	4%
CTRL-N	383	382	382	379	379	376	374	372	371	3%
Total	2217	2081	2062	2037	2018	1999	1982	1957	1912	16%

Only customers that accepted their treatment and remained on it and customers that decided to stop participating after being placed on their treatment status.
*Calculated from January to September, 2013.

Table **3-5**: Descriptive statistics.

	2012	2013
	Average Hourly Load (kWh/h)	
CPP	0.8216 (0.8385)	0.7883 (0.8343)
CPP-I	0.776 (0.8363)	0.7692 (0.8025)
CTR	0.8391 (0.9012)	0.7906 (0.8392)
CTR-I	0.7931 (0.8436)	0.7719 (0.8368)
CTRL-N	0.8332 (0.8613)	0.7691 (0.7902)
CTRL	0.8185 (0.8817)	0.7909 (0.8367)
Total	0.8222 (0.8713)	0.782 (0.825)

Note: Only customers that accepted their treatment and remained on it and customers that decided to stop participating after being placed on their treatment status.

Table 3.5 shows that customers in the dataset who accepted their treatment and remained on it or who decided to stop participating after being placed on their treatment had an average load of 0.82kWh/h during 2012 with a standard deviation of 0.87kWh/h. The same statistic for 2013 is 0.78kWh/h with a standard deviation of 0.83kWh/h. In both cases, the large standard deviations reflect the diversity of customers in the sample. This last feature is also present in each group.

Average load shapes for treatment and control groups

Table 3.6 presents means and standard deviations of hourly load for each group and for peak and non-peak hours during 2012 and 2013. The third and sixth columns tally the number of customers in each group (only customers that accepted their treatment and remained on it and customers that decided to stop participating after being placed on their treatment status). It must be noted that, for the purpose of comparison, non-peak hours are defined as follows: 1p.m. to 6p.m. on non-critical event days. Therefore, it is possible to analyze the potential differences between groups during comparable periods.

First, it must be noted that average hourly loads during peak hours (for all groups) in 2013 are higher than those in 2012. This is probably a consequence of the season in which critical event days took place. During the fall of 2012 (temperatures between 68-77°F) and in the summer of 2013 (temperatures between 69-90°F).

Table 3.6 shows that during peak hours, relative to the control group, customers that received some kind of treatment (with the exception of the CPR group during 2013) reduced their consumption of electricity. This could be potential evidence of the causal effect of the program; however, as the table shows, during non-peak hours there are statistically significant differences between the treated and control groups. In this sense, these pre-existing differences must be taken into account in order to appropriately evaluate the impact of the program.

Table **3-6**: Average hourly load per period (kWh/h).

		2012		2013	
		Peak Hours	Non-Peak Hours	Peak Hours	Non-Peak Hours
		(1)	(2)	(3)	(4)
CPP	(A)	0.6549	0.9422	1.1169	0.8789
		(0.692)	(0.9422)	(1.147)	(0.9412)
CPP-I	(B)	0.6058	0.9038	1.0458	0.8517
		(0.6681)	(0.9638)	(0.9833)	(0.8827)
CPR	(C)	0.6964	0.9713	1.2129	0.8814
		(0.7605)	(1.0274)	(1.2042)	(0.9345)
CPR-I	(D)	0.6484	0.9187	1.1333	0.8605
		(0.6848)	(0.9509)	(1.1176)	(0.9165)
CTRL-N	(E)	0.7143	0.9515	1.1326	0.8462
		(0.7159)	(0.9558)	(1.002)	(0.8673)
CTRL	(F)	0.7179	0.9447	1.1953	0.875
		(0.7813)	(1.0168)	(1.1591)	(0.9374)
Difference	(A) - (F)	-0.0631*	-0.0025	-0.0784*	0.0039
		(0.0126)	(0.0028)	(0.0116)	(0.0025)
Difference	(B) - (F)	-0.1121*	-0.0409*	-0.1495*	-0.0233*
		(0.0161)	(0.0038)	(0.0126)	(0.0029)
Difference	(C) - (F)	-0.0215*	0.0266*	0.0175	0.0063*
		(0.0113)	(0.0024)	(0.0124)	(0.0026)
Difference	(D) - (F)	-0.0696*	-0.0259*	-0.0621*	-0.0146*
		(0.0129)	(0.0028)	(0.0143)	(0.0031)
Difference	(E) - (F)	-0.0036	0.0068*	-0.0627*	-0.0288*
		(0.0127)	(0.0028)	(0.0118)	(0.0026)

Note: Columns of the top panel present means and standard deviations (in parentheses) of hourly load for each group per period. The bottom panel presents the differences of means relative to the control group (row F) with standard deviations in parenthesis. Periods considered: August 2012 - December 2012 and May 2013 - September 2013.

*Statistically significant at 0.10 level

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A major concern regarding the analysis carried out in this study is that customers treated could be different from those in the control group and that these differences may be correlated with energy consumption. Even when they were randomly assigned to each group, this is still a potential problem. As it was mentioned above, the encouragement to take the treatment rather than the treatment itself was randomly assigned to customers. For example, those who accepted the CPP rate might be more careful about energy use than those who belong to the control group. In this case, the correlation between the treatment rate and energy consumption would be confounded with that individual effect. In principle, many of the types of unobservable characteristics that may confound identification are those that vary across customers but are fixed over time. A common method of controlling for time-invariant unobserved heterogeneity is to use panel data and estimate difference-in-differences models.

The key identification assumption is that the change in electricity consumption in control customers is an unbiased estimate of the counterfactual (i.e. the amount of electricity consumed by treated customers in the absence of the treatment). While we cannot directly test this assumption, we can analyze whether the evolution of electricity consumption for the control and treated customers was similar during non-peak hours. If the secular trends are similar during non-peak hours, then it is likely that they would have been the same during peak-hours if the treated customers had not a different rate structure.

Table 3-7 presents households' electricity consumption from January 2012 to September 2012 divided by three periods (Jan-Mar, April-Jun and Jul-Sep). During the period Jan-Mar, customers were just being assigned to their treatment groups hence showing pre-treatment behavior. From Table 3-7 it can be inferred that previous to facing different tariff structures customers in different groups had similar average electricity consumption and as a consequence it can be assumed that differences in electricity consumption during peak hours were only due to treatments.

Table **3-7**: Average hourly load per period (kWh/h).

	Jan-Mar	April-Jun	July-Sep
CPP	0.7190 (0.8652)	0.7601 (0.8312)	0.9089 (0.9502)
CPP-I	0.6724 (0.6428)	0.7302 (0.7603)	0.8468 (0.8329)
CTR	0.6771 (0.7257)	0.7165 (0.7466)	0.8609 (0.8502)
CTR-I	0.6801 (0.7818)	0.7502 (0.8212)	0.8334 (0.8281)
CTRL-N	0.6617 (0.6903)	0.7327 (0.7858)	0.8772 (0.8890)
CTRL	0.6774 (0.6824)	0.7709 (0.8028)	0.8797 (0.8594)

Further, figures 3.2 and 3.3 suggest that the evolution of electricity consumption during an average non-critical day for each group was similar. Although the levels of consumption are different among groups (as already noted from Table 3.6), the trends are parallel. Similar information is provided in Figures 3.4 and 3.5. The evolution of electricity consumption is similar among groups before an event took place. During peak-hours the average behavior of each group diverges and there is on average, relative to the control group, a reduction on consumption in the treated groups. This implies that the consumption of electricity for treatment and control groups had similar time trends during non-peak hours, which validates the difference-in-differences identification strategy used in this study.

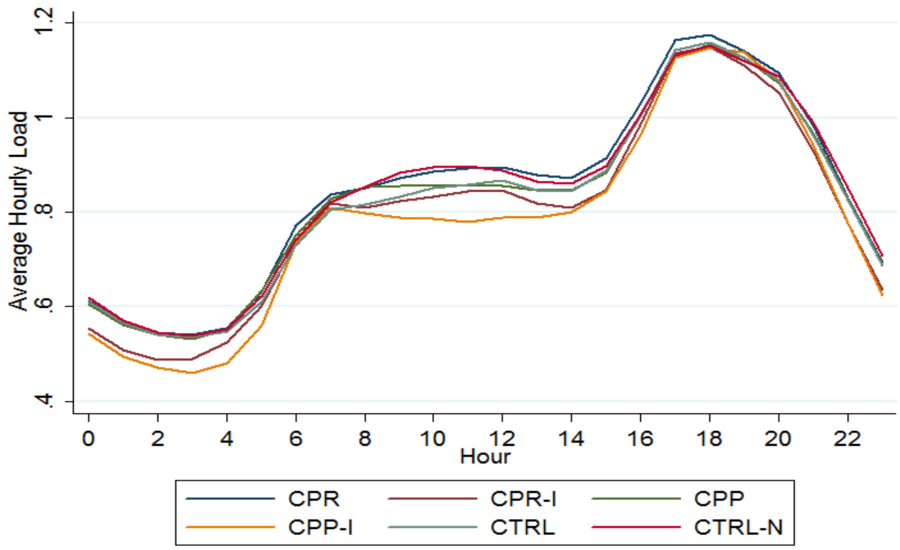

Figure **3-2**: Average non-critical event day (2012).

Note: Period August 2012 – December 2012. Customers who declined to participate are not included.

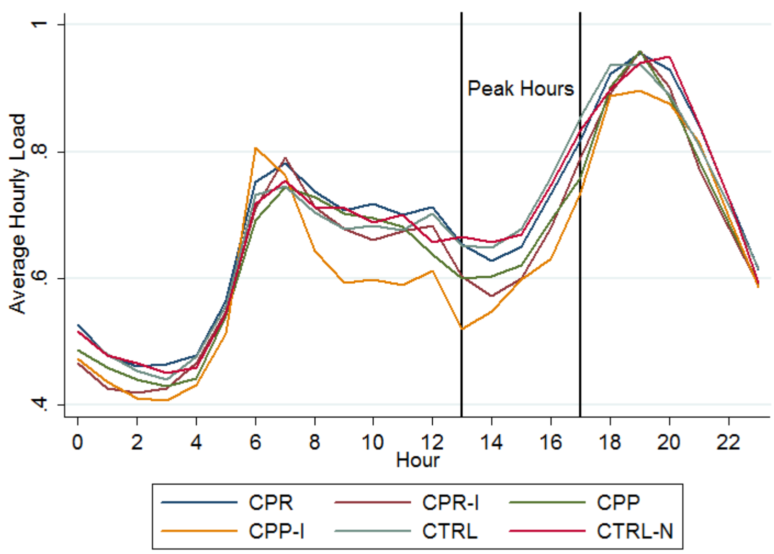

Figure **3-3**: Average critical event day (2012).

Note: Period August 2012 – December 2012. Customers who declined to participate are not included.

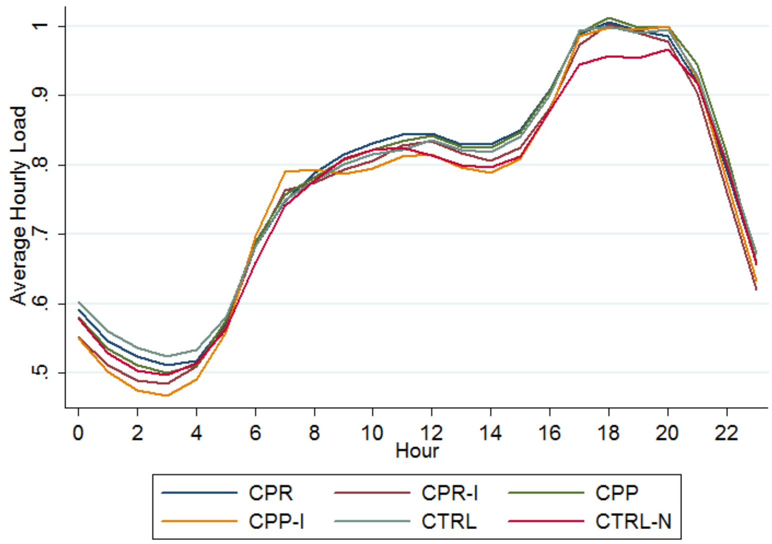

Figure **3-4**: Average non-critical event day (2013).

Note: Period May 2013 – September 2013. Customers who declined to participate not included.

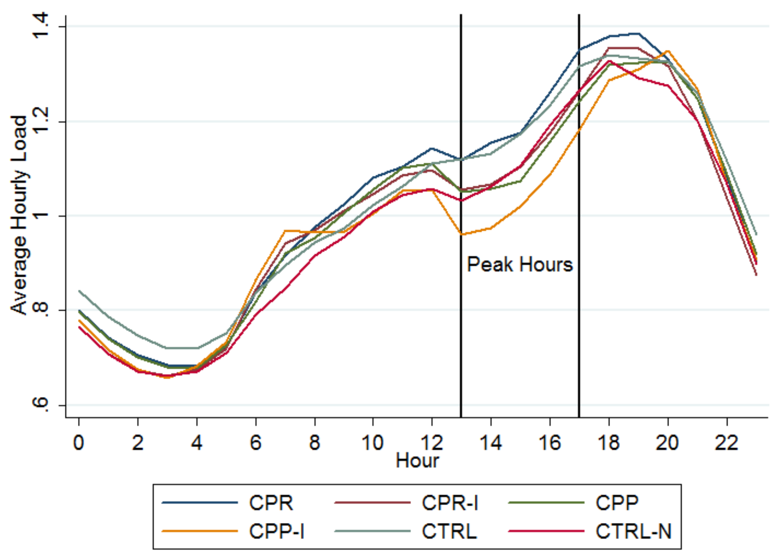

Figure **3-5**: Average critical event day (2013).

Note: Period May 2013 – September 2013. Customers who declined to participate not included.

Regression Model

The main objective of this study is to identify the causal effect of different types of electricity pricing structures on electricity consumption. As it was mentioned above, although the program was a Randomized Encouragement Design (RED), it was not possible to implement an instrumental variable approach due to data availability issues. In other words, if the dataset had included all 16,545 customers who were randomly encourage to participate in the study, we could had estimated the following regression

$$hourlyload_i = \alpha_0 + \sum_{j=1}^{J} \alpha_j Treat_i^j + \varepsilon_i$$

Where: $\mathrm{hourlyload_i}$ would be the average hourly load of customer i during peak hours and $\mathrm{Treat_i^j}$ a dummy variable that equals 1 if customer i is in treatment group j. As $\mathrm{Treat_i^j}$ is an endogenous variable, we would use $\mathrm{encourage_i^j}$ as an instrumental variable ($\mathrm{encourage_i^j}$ would equal 1 if customer i was encouraged to participate in the group j)[1]. Given that encouragement to participate was randomly assigned, this approach is valid in the sense, that the estimation of the α_j parameters by Two-Stage Least Squares would be consistent.

Instead, due to the data limitation already mentioned, this study proposes to evaluate the program using a difference-in-differences approach. The previous section showed that the assumptions behind this estimation strategy are reasonable in the sense that the change in electricity consumption (between peak and non-peak hours) in control customers is an unbiased estimate of the counterfactual.

Therefore, the main regression model takes the following form:

$$Hourly\ Load_{it} = \sum_{j=1}^{5} \beta_j Treatment_{it}^j + C_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

[1] The coefficient estimated that arises from this strategy is equivalent to estimating the Intention to Treat (ITT) effect (i.e. regressing the dependent variable on the instrument) and dividing it by the compliance rate.

Where:

Hourly Load_{it} is the hourly load for customer i for hour t;

$\text{Treatment}_{it}^{j}$ is a dummy variable that equals 1 for critical peak hours if customer i belongs to treatment group j;

C_i is a customer fixed effect;

λ_t is an hour fixed effect;

ε_{it} is the error term.

The parameters of interest are β_j with $j = 1, \dots, 5$; each one representing the effect of one of the treatment rate structures described above. Customer fixed effects are included in order to control for time-invariant influences (observables and/or unobservable characteristics). Also, hour-of-sample fixed effects are included that control for aggregate effects (such as weather conditions) that could be correlated with electricity consumption. It is important to note that λ_t does not represent 24 constants; instead, $t = (1, \dots, 24) * D$ where D is the number of days in the sample. Moreover, equation (1) was estimated separately for each year.

As an alternative to equation (1), treatment fixed effects could be included (necessarily omitting customer fixed effects). In this case, the model takes the following form,

$$\text{Hourly Load}_{it} = \sum_{j=1}^{5} \beta_j \text{Treatment}_{it}^{j} + \sum_{j=1}^{5} \propto_j T_i^j + \lambda_t + \varepsilon_{it} \qquad (2)$$

Where:

Hourly Load_{it}, $\text{Treatment}_{it}^{j}$ and λ_t are defined as was mentioned above and T_i^j with $j = 1, \dots, 5$ is a dummy variable that equals 1 for customer i on treatment j.

It is important to note that if there were time-invariant heterogeneity within each group, the estimation of the parameters in equation (2) would be biased. This is why the model in equation (1) is the preferred one and the alternative proposed could be used as a robustness check.

Results

Table 3.7 presents the regression results. Columns (1), (3) and (5) correspond to the estimation of equation (1) which includes customer fixed effects and hour fixed effects. Columns (2), (4) and (6) correspond to the estimation of equation (2) which includes treatment fixed effects and hour fixed effects. Clustered standard errors at the customer level are shown in parenthesis.

First it must be noted that, in any case, there are not systematic and significant differences between results of the estimation of the equation (1) and results associated with equation (2). Both kinds of models lead to similar results.

Table **3-8**: Effects of different electricity pricing structures on electricity consumption (kWh/h).

	2012		2013		Both Years	
	(1)	(2)	(3)	(4)	(5)	(6)
CPR	-0.0423**	-0.0424**	0.0150	0.0175	-0.0113	-0.0118
	(0.0207)	(0.0207)	(0.0409)	(0.0412)	(0.0299)	(0.0313)
CPR-I	-0.0442*	-0.0447*	-0.0442	-0.0436	-0.0418	-0.0420
	(0.0239)	(0.0239)	(0.0473)	(0.0474)	(0.0351)	(0.0367)
CPP	-0.0664***	-0.0658***	-0.0794**	-0.0790**	-0.0725***	-0.0777**
	(0.0240)	(0.0240)	(0.0377)	(0.0378)	(0.0304)	(0.0314)
CPP-I	-0.0748**	-0.0696**	-0.132***	-0.131***	-0.121***	-0.118***
	(0.0309)	(0.0313)	(0.0414)	(0.0415)	(0.0347)	(0.0354)
CTRL-N	-0.0176	-0.0185	-0.0410	-0.0420	-0.0406	-0.0410
	(0.0246)	(0.0246)	(0.0382)	(0.0383)	(0.0306)	(0.0308)
Customer Fixed Effects	Yes	No	Yes	No	Yes	No
Treatment Fixed Effects	No	Yes	No	Yes	No	Yes
Hour Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,811,956	7,811,956	7,259,802	7,259,802	15,071,758	15,071,758

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012 and from May 2013 to September 2013. Only customers who have accepted their treatment status at the beginning of each period. Clustered standard errors at the customer level are in parenthesis.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

As column (1) of Table 3.7 shows, during 2012 all types of electricity pricing structures (excluding the treatment group whose members remained on the default rate but were notified of peak-time events) have a statistically significant impact on electricity consumption. The most effective treatment seems to be the CPP-I; the average reduction of electricity usage during peak hours is about -0.075 kWh/h. The second most effective is the CPP treatment; members of this group show a slightly lower reduction of -0.067 kWh/h. Meanwhile, for the CPR and CPR-I groups, the impact of the interventions is of the same magnitude; around -0.042kWh/h and -0.044 kWh/h respectively.

For the year 2013, column (3) of Table 3.7 shows relatively different results. In particular, the impact of the CPR and CPR-I treatments is not statistically significant. Also the sign of the point estimate of the effect of the CPR treatment is not as expected. However, the impact of the CPP and CPP-I treatments on electricity consumption is larger than those for 2012 and remains statistically significant. Finally, when the estimation is carried out for both years, the results are similar to those obtained for 2013. This is probably due to the fact that most of the critical events (10 out of 14) occurred during that year.

In summary, results presented in Table 3.7 suggest that, at the beginning of the study and particularly during the first events in 2012, the intervention had a significant impact on electricity usage, and the CPP and CPP-I were the most effective treatments. During 2013, the impact of these latter treatments increased, while the impact of the CPR and CPR-I treatments vanished.

To further analyze the response to different treatments, Table 3.8 and Table 3.9 show the effect of each treatment on each critical peak event. During 2012, results suggest that the impact of the intervention was stronger during the first event of the year than during the rest of the events. Except for the CPP and CTRL-N treatments, the rest of the groups show high and statistically significant responses to the treatment intervention on the first critical event.

Table **3-9**: Effect of different treatments on energy consumption by critical event.

	2012 Events			
	1	2	3	4
CPR	-0.0554*	-0.0362	-0.0354	-0.0422
	(0.0334)	(0.0305)	(0.0299)	(0.0302)
CPR-I	-0.112***	-0.0189	-0.0153	-0.0304
	(0.0362)	(0.0349)	(0.0348)	(0.0357)
CPP	-0.0605	-0.0586*	-0.0693**	-0.0771**
	(0.0382)	(0.0330)	(0.0341)	(0.0337)
CPP-I	-0.124***	-0.0763*	-0.0510	-0.0485
	(0.0473)	(0.0421)	(0.0417)	(0.0436)
CTRL-N	0.00822	-0.0295	-0.00516	-0.0438
	(0.0382)	(0.0358)	(0.0359)	(0.0338)

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012. Only customers who have accepted their treatment status at the beginning the period. Customer fixed effects and hour fixed effects are included. Clustered standard errors at the customer level are in parenthesis.*** p<0.01, ** p<0.05, * p<0.1.

The impact of the CPR and CPR-I groups diminished significantly from the second through the fourth critical event. Something relatively similar occurred in the case of the CPP-I treatment; the effect of the latter is not statistically significant during the third and fourth events. For the CPP group the effect is significant for the second, third, and fourth critical events with a stable point estimate throughout the events.

Table **3-10**: Effect of different treatments on energy consumption by critical event.

	2013 Events									
	1	2	3	4	5	6	7	8	9	10
CPR	-0.00701	0.0840	0.0510	-0.0199	-0.00343	-0.0209	0.00180	-0.0126	0.0549	0.0227
	(0.0606)	(0.0585)	(0.0591)	(0.0621)	(0.0628)	(0.0722)	(0.0346)	(0.0495)	(0.0529)	(0.0472)
CPR-I	-0.0575	0.00805	-0.0421	-0.121*	0.00962	-0.0964	-0.0108	-0.0529	-0.0519	-0.0265
	(0.0750)	(0.0719)	(0.0701)	(0.0721)	(0.0732)	(0.0806)	(0.0433)	(0.0537)	(0.0537)	(0.0544)
CPP	-0.0656	-0.0847	-0.0896	-0.0894	-0.0691	-0.155**	-0.0261	-0.0987**	-0.0667	-0.0480
	(0.0578)	(0.0534)	(0.0556)	(0.0612)	(0.0624)	(0.0682)	(0.0330)	(0.0420)	(0.0437)	(0.0481)
CPP-I	-0.0982	-0.0525	-0.155***	-0.222***	-0.182***	-0.262***	-0.0294	-0.115**	-0.0551	-0.144***
	(0.0642)	(0.0628)	(0.0597)	(0.0615)	(0.0622)	(0.0722)	(0.0376)	(0.0454)	(0.0522)	(0.0486)
CTRL-N	-0.0586	-0.0451	-0.0399	-0.111*	-0.0647	-0.0578	-0.0319	-0.0191	0.0278	-0.00845
	(0.0565)	(0.0540)	(0.0560)	(0.0607)	(0.0585)	(0.0710)	(0.0335)	(0.0419)	(0.0465)	(0.0451)

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From May 2013 to September 2013. Only customers who have accepted their treatment status at the beginning of the period. Customer fixed effects and hour fixed effects are included. Clustered standard errors at the customer level are in parenthesis.*** p<0.01, ** p<0.05, * p<0.1.

From Table 3.9 one cannot distinguish a clear response pattern to treatments. First, members of the CPR group behaved differently from the control group during critical events. Also, surprisingly, the CPR-I treatment only had a strong effect on electricity usage during the fourth event (during the same event, the CTRL-N shows a unique statistically significant response over the whole study). Meanwhile, the CPP group shows a high and statistically significant response during the sixth and eight events.

During 2013, even when the point estimates are not stable, the only group that responds regularly to treatment is the CPP-I group. As it is shown in Table 3.9, during 6 out of the 10 events, members of this group use a statistically lower amount of electricity than the control group during critical peak days.

To summarize the results presented, except for the first critical event in 2012, the pricing structures associated with the CPR and the CPR-I treatments are not effective at reducing consumption of electricity during peak hours. A similar conclusion could be made for the CTRL-N treatment. Unlike the latter treatments, CPP and CPP-I treatments are effective, although the magnitude of the effect is not persistent over time.

Table 3.10 shows the impact of treatment on electricity consumption during peak periods by income level. During 2012, customers belonging to medium and high income levels (with the exception of the CTRL-N group) showed statistically significant responses during peak periods with high income customers showing the highest reductions in electricity consumption. During 2013, although the majority of estimations were of the expected sign, these are not statistically significant, implying that income did not play an important role on consumer response to changes in electricity prices. When the estimation is carried out for both years, high income customers (with the exception of those in the CPP-I group) showed statistically significant reductions in electricity consumption during peak hours. This result might be the consequence of high income customers having more discretionary load to adjust when dynamic tariffs are implemented.

Table **3-11**: Effect of different treatments on electricity consumption by income level.

	2012	2013	Both Years
CPR			
Low Income	0.0498*	-0.0673	-0.0252
	(0.0265)	(0.0534)	(0.0382)
Medium Income	-0.0631**	0.0151	-0.0202
	(0.0254)	(0.0539)	(0.0379)
High Income	-0.149***	-0.111	-0.131***
	(0.0372)	(0.0740)	(0.0478)
CPR-I			
Low Income	0.0824**	-0.0602	0.00261
	(0.0388)	(0.0699)	(0.0508)
Medium Income	-0.0638**	-0.0611	-0.0722
	(0.0295)	(0.0646)	(0.0474)
High Income	-0.147***	-0.225*	-0.203***
	(0.0466)	(0.115)	(0.0783)
CPP			
Low Income	0.0172	-0.0268	-0.0192
	(0.0464)	(0.0615)	(0.0496)
Medium Income	-0.0885***	-0.120**	-0.114***
	(0.0297)	(0.0471)	(0.0382)
High Income	-0.133***	-0.164**	-0.160**
	(0.0473)	(0.0774)	(0.0643)
CPP-I			
Low Income	0.0252	-0.209***	-0.159***
	(0.0514)	(0.0579)	(0.0498)
Medium Income	-0.0658*	-0.107*	-0.0968**
	(0.0393)	(0.0545)	(0.0461)
High Income	-0.262***	-0.136	-0.145
	(0.0795)	(0.112)	(0.0996)
CTRL-N			
Low Income	0.0160	-0.0882	-0.0619
	(0.0355)	(0.0556)	(0.0418)
Medium Income	0.000952	0.00233	0.00230
	(0.0344)	(0.0541)	(0.0440)
High Income	-0.152***	-0.0808	-0.114*
	(0.0590)	(0.0802)	(0.0690)
Customer Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Observations	6,340,760	5,879,299	12,220,059

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012 and from May 2013 to September 2013. Only customers who have accepted their treatment status at the beginning of each period. Clustered standard errors at the customer level are in parenthesis.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.11 presents the estimated effect of the treatment on customer responses during critical peak events by education level. In 2012, households with a high level of education showed statistically significant reductions in electricity consumption (the only exception were households enrolled in the CTRL-N group). The higher reductions were obtained for the CPP-I and CPP groups with -0.113kWh/h and -0.109kWh/h respectively. A similar trend was observed in 2013, but that year the estimations for the CPR, CPR-I, and CPP groups were not statistically significant. The CPP-I and CPP groups continue showing higher reductions in consumption with -0.231kWh/h and -0.161kWh/h respectively. When the estimation was carried out for both years, the larger statistically significant effects were obtained for households with high education under the CPP-I and CPP rates (-0.231kWh/h and -0.161kWh/h respectively). Since education is often highly correlated with income and both variables are highly correlated with electricity consumption, this result was expected. In order to account for these potential collinearities, a factor analysis of customers’ responsiveness to critical events and different socioeconomic variables will be conducted in the following chapter of this study. This analysis will result in an estimation of the role that clusters of variables play in defining customer response patterns.

Table **3-12**: Effect of different treatments on energy consumption by education level.

	2012	2013	Both Years
CPR			
Low Education	0.0249	-0.0105	-0.00191
	(0.0467)	(0.0899)	(0.0630)
Medium Education	-0.0285	0.0340	0.00653
	(0.0222)	(0.0466)	(0.0326)
High Education	-0.0565**	0.00383	-0.0231
	(0.0272)	(0.0609)	(0.0432)
CPR-I			
Low Education	0.0934***	-0.0440	0.00322
	(0.0321)	(0.0983)	(0.0732)
Medium Education	-0.0275	0.0165	-0.00273
	(0.0305)	(0.0622)	(0.0448)
High Education	-0.0837***	-0.104	-0.103**
	(0.0295)	(0.0641)	(0.0468)
CPP			
Low Education	0.202***	-0.00223	0.0543
	(0.0665)	(0.105)	(0.0857)
Medium Education	-0.0694**	-0.0274	-0.0417
	(0.0287)	(0.0417)	(0.0339)
High Education	-0.109***	-0.161***	-0.157***
	(0.0312)	(0.0519)	(0.0422)
CPP-I			
Low Education	0.0525**	0.230	0.211
	(0.0232)	(0.150)	(0.134)
Medium Education	-0.0471	-0.0978**	-0.0891**
	(0.0391)	(0.0490)	(0.0420)
High Education	-0.113***	-0.231***	-0.206***
	(0.0426)	(0.0519)	(0.0432)
CTRL-N			
Low Education	-0.0288	0.237	0.141
	(0.0529)	(0.150)	(0.114)
Medium Education	-0.00571	-0.0176	-0.0175
	(0.0294)	(0.0447)	(0.0357)
High Education	-0.0295	-0.0991**	-0.0882**
	(0.0369)	(0.0471)	(0.0394)
Customer Fixed Effects	Yes	Yes	Yes
Hour Fixed Effects	Yes	Yes	Yes
Observations	7,681,272	7,166,591	14,847,863

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012 and from May 2013 to September 2013. Only customers who have accepted their treatment status at the beginning of each period. Clustered standard errors at the customer level are in parenthesis.*** p<0.01, ** p<0.05, * p<0.1.

Discussion

Multiple potential benefits are associated with the adoption of time-varying tariffs. Participants can benefit from lower electricity prices during peak periods which produce savings in their electricity bills (depending on their consumption patterns). The market as a whole could benefit from DR programs by avoiding the dispatch of the last less efficient and more expensive generator and by delaying the expansion of infrastructure related to increments in peak load. Benefits could also include increased reliability due to decreased system contingencies. Market power may be diminished by taking away the ability of an expensive marginal plan to significantly alter the overall system generating cost. Finally, if a persistent response to price signals is achieved, it may result in decreased required reserve margins.

Utilities are testing time-varying tariffs as tools to incentivize reductions in electricity consumption during hours of high demand. Different studies have reported that customers do respond to price signals (Faruqui et al. 2014, Herter et al. 2007). However, some studies have also reported that responses are not persistent across events with similar dynamic prices and weather conditions (Faruqui et al. 2009, Faruqui et al. 2012). In the case I explored, with the exception of the first critical event in 2012, the pricing structures associated with the CPR and CPR-I treatments do not seem to be effective at reducing electricity consumption during critical peak events. A similar conclusion can be made about the CTRL-N treatment. Unlike the latter treatments, CPP and CPP-I treatments seem to be effective. However, the magnitude of the responses to critical events for these treatment groups varies significantly across events and years.

More information on the factors determining customer responsiveness to time-varying tariffs is needed in order to gain a better understanding of the real potential of time-based demand response programs. Based on the evidence obtained in this study, the great variability of responses to critical events makes it difficult to implement these tariffs at full scale. The difficulty of predicting the level of response to critical events over a range of prices makes the participation of economic-based DR resources in wholesale markets difficult. Consequently, if a better understanding of customer responses to critical prices is not gain as more data from multi-year pilot studies becomes available, economic-based demand response programs should not be pursued, and instead, other alternatives like incentive-based DR programs and distributed generation should continue to be expanded.

Chapter 4

Heterogeneous responses to critical peak events: a factor analysis approach

Introduction

The main objective of this section is to analyze and estimate the potential heterogeneity in customer response to different types of electricity pricing structures. As it was mentioned in previous sections, during 2012 and 2013, eligible customers in the vicinity of Rutland, VT, were assigned to one of eight different treatment groups. In order to analyze whether the response to these treatments differs by socioeconomic characteristics, a Descriptive Factor Analysis was performed on socioeconomic variables and electricity consumption. The relevant factors obtained from that analysis were used to estimate a regression model which resembles a difference-in-difference-in-differences approach.

Usually, the literature on electricity consumption uses Factor Analysis or Principal Component Analysis as a method to identify the number of variables that better explain the variability observed in energy usage. However, in spite of incorporating a Factor Analysis, the main objective of this study is not to identify the potential latent variables that maximize the explained variability in electricity consumption. Rather, the purpose is to evaluate whether the impact of different pricing treatments over energy usage depends on certain factors commonly associated with electricity consumption.

Therefore, incorporating the factor solution in a difference-in-difference regression model (that leads to a difference-in-difference-in-difference model) is considered as the most appropriate way of analyzing and estimating the potential heterogeneity in customer response to the program implemented by Green Mountain Power. In this manner, the results obtained in this section would be complementary to the impact evaluation performed in previous sections.

Factor Analysis

Given a set of observed and correlated variables, Factor Analysis is a statistical technique used to find a few common unobservable or latent variables, called factors, that linearly reconstruct each observed variable. The variability observed among a number of variables is assumed to be the reflection of the variation in a smaller number of factors. Therefore, in a context where multi-collinearity is a potential problem, Factor Analysis turns out to be a useful method for data reduction.

Formally, in factor analysis the observed variables $y_1, \dots, y_p$ are represented as linear combinations of a few random factors $f_1, \dots, f_m$ $(m < p)$ in the following way,

$$
\begin{gathered}
y_1 - \mu_1 = \lambda_{11} f_1 + \cdots + \lambda_{1m} f_m + \varepsilon_1 \\
\vdots \\
y_p - \mu_p = \lambda_{p1} f_1 + \cdots + \lambda_{pm} f_m + \varepsilon_p
\end{gathered}
$$

Where $\mu_1, \dots, \mu_p$ are the means of each observed variable; $\varepsilon_1, \dots, \varepsilon_p$ are error terms that account for the part of the variable that is unique (not in common with the other variables) and λ_{ij} are called loadings and serve as weights, showing how each y_i individually depends on the factor f_j.

It can be shown that under certain assumptions,

$$\mathrm{corr}(y_i, f_j) = \lambda_{ij}$$

Hence each loading represents the correlation of a variable with a specific factor. Intuitively, the main idea behind Factor Analysis consists of representing the variability between the observed variables by means of the loadings associated with each factor. Further, from the model presented, it could be shown that the variability of y_i can be partitioned into a component due to the common factors, called communality, and a component unique to y_i, called the specific variance or uniqueness.

There are several methods or approaches used for estimating loadings and communalities. The technique used in this study is commonly called Principal Component Analysis. Its name comes from the fact that the columns of the estimated matrix of loadings are proportional to the eigenvectors of the sample correlation matrix, so that the loadings on the jth factor are proportional to coefficients in the jth principal component (Rencher, 2002).

Data and Methodology

This study uses household level hourly electricity consumption in the city of Rutland, VT, for the years 2012 and 2013. In addition to information on energy usage at the household level, information on socioeconomic characteristics, ownership of appliances and other variables are included.

The Factor Analysis was conducted using a multiple-step process. First, a Principal Component Analysis was performed using all the selected socioeconomic variables including electricity consumption. In this manner, not only relevant factors and associated variables could be identified but also, and specially, the relevance of each factor in terms of correlation with electricity consumption could be ensured. Therefore, certain criteria were applied to include or exclude factors (and associated variables) in the following steps of the analysis. In particular, if the correlation between electricity consumption and a factor were below 0.1, the corresponding factor and the associated variables were excluded from the analysis. Once the relevant factors were identified, a Principal Component Analysis was performed excluding hourly electricity consumption. The rotated factor solution was used to estimate standardized factor scores which were then included in a difference-in-difference regression model.

Since the sample correlation matrix is an essential input in factor analysis, it is important to correctly estimate the correlation between each pair of variables. The data used in this study consists of continuous, categorical and dichotomous variables. Therefore, in order to avoid potential biases in the estimation of correlations, polychoric correlations were computed (Lee et al., 1995; Kolenikov and Angeles, 2004).

Data

The sample used contains information on hourly electricity consumption from customers divided into six groups, each designated for a different pricing treatment during declared peak events. The factor analysis was conducted using observations that covers two periods: from August 2012 to December 2012 and from May 2013 to September 2013. Additionally, the sample contains information on demographic and socioeconomic characteristics of the households that were included in the analysis.

The variables included in the first step of the factor analysis were: an index of apparent temperature per hour (HI), number of degrees above 65 Fahrenheit per hour (Cooling Hours), number of Air Conditioners in the house (ACs), a dichotomous variable that takes the value 1 if the house has a Central Air Conditioner and 0 otherwise (CAC), a dichotomous variable that takes the value 1 if the house has Ceiling Fans and 0 otherwise (CFs), a dichotomous variable that takes the value 1 if the house has a Dehumidifier and 0 otherwise (DEH), a dichotomous variable that takes the value 1 if the house has a Programmable Thermostat and 0 otherwise (PT), number of people living in the house (People), a dichotomous variable that takes the value 1 if the house has an Electric Clothes Dryer and 0 otherwise (ECD) and a dichotomous variable that takes the value 1 if the house has an Electric Stove and 0 otherwise (ES).

Table **4-1**: Descriptive Statistics.

Variable	Mean	Std. Dev.	Min.	Max.
HI	51.4765	20.0022	-19.7	88.2
Cooling Hours	2.7742	4.9912	0	27
ACs	1.8132	0.9687	1	5
CAC	0.0138	0.1167	0	1
CFs	0.7036	0.4567	0	1
DEH	0.4015	0.4902	0	1
PT	0.4650	0.4988	0	1
People	2.5001	1.2681	1	9
ECD	0.7230	0.4475	0	1
ES	0.8564	0.3506	0	1
Hourly Load	0.8673	0.8694	0	15.3

Periods: August 2012 to December 2012 and May 2013 to September 2013. Number of customers (households): 1373. Number of observations: 9,089,457.

Table 4.1 shows descriptive statistics for the variables used in the first step of the factor analysis. The sample contains information on 1,373 households. The average household has almost two Air Conditioners and is composed of 2.5 members. Moreover, 70% of the sample has ceiling fans, 40% has a Dehumidifier, 47% has a Programmable Thermostat and approximately 1% has a Central Air Conditioner. Also, 72% and 86% of the sample has an Electric Clothes Dryer and an Electric Stove respectively. Finally, the average hourly load is 0.87 kWh/h with standard deviation of 0.87 kWh/h (suggesting an important degree of variability among households).

The estimated polychoric correlation matrix is shown in Table 4.2. As it can be seen, electricity consumption is mainly correlated with temperature (especially with the variable Cooling Hours), number of Air Conditioners, the presence of Ceiling Fans and Electric Clothes Dryer and the number of people living in the house. On the contrary, it does not seem to be correlated with the ownership of an Electric Stove or a Programmable Thermostat. Also, it is mildly correlated with having a Central Air Conditioner and a Dehumidifier.

Additionally, as it was expected, having a Central Air Conditioner is negatively correlated with the number of Air Conditioners in the house and positively correlated with having a Programmable Thermostat. Also, the number of people living in the house is positively correlated with the number of ACs and the ownership of an Electric Clothes Dryer and Ceiling Fans.

Table **4-2**: Estimated Polychoric Correlation Matrix.

	H. Load	HI	C. Hours	ACs	CAC	PT	CFs	ECD	ES	DEH	People
H. Load	1.000										
HI	0.049	1.000									
C. Hours	0.153	0.640	1.000								
ACs	0.179	0.000	0.000	1.000							
CAC	0.059	-0.001	-0.001	-0.190	1.000						
PT	0.030	-0.004	-0.002	0.074	0.086	1.000					
CFs	0.113	0.006	0.003	0.134	0.088	0.055	1.000				
ECD	0.187	0.008	0.004	0.199	-0.039	0.089	0.186	1.000			
ES	0.003	0.000	0.000	-0.053	-0.060	-0.013	-0.086	0.310	1.000		
DEH	0.091	0.004	0.002	0.096	0.040	0.144	0.126	0.211	0.112	1.000	
People	0.254	-0.002	-0.001	0.340	0.044	0.047	0.158	0.202	-0.026	0.102	1.000

The correlation matrix presented in Table 4.2 was used as an input for the first step of the Factor Analysis. The obtained results are shown in Table 4.3.

The obtained four factor solution accounts for 55.1% of the variance among the 11 variables. In this study I assume that a variable is specially associated with a specific factor when the corresponding loading is greater than or equal to 0.40. In this manner, Factor 1 could be interpreted as representing structural characteristics of the household (it is mainly associated with the number of Air Conditioners, the presence of Ceiling Fans and the number of people living in the house). Factor 2 is associated with climate conditions, Factor 3 with owning special appliances (Electric Clothes Dryer, Electric Stove and Dehumidifier) and Factor 4 with owning a Central Air Conditioner and a Programmable Thermostat. All factors, except Factor 3, are highly correlated with electricity consumption. Since the correlation of electricity consumption with Factor 3 is less than 0.1, this factor and the associated variables are excluded from the analysis.

Table **4-3**: Rotated factor loadings and unique variances.

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
HI	-0.0159	**0.8924**	0.0054	-0.0053	0.2033
Cooling Hours	0.0208	**0.9067**	-0.0005	0.0058	0.1774
ACs	**0.7485**	-0.0282	0.0190	-0.2600	0.3711
CAC	-0.1491	0.0108	-0.1261	**0.7763**	0.3591
PT	0.0929	-0.0311	0.1457	**0.4760**	0.7426
CFs	**0.4218**	-0.0172	-0.0160	0.3995	0.6619
ECD	0.3624	0.0010	**0.6973**	0.0568	0.3792
ES	-0.1901	0.0092	**0.8119**	-0.1512	0.2818
DEH	0.1773	-0.0144	**0.4712**	0.3619	0.6153
People	**0.7156**	-0.0170	0.0033	0.0711	0.4826
Hourly Load	0.5196	0.2031	0.0695	0.1529	0.6606

Notes: Factor Analysis Solution based on Polychoric Correlation Matrix. Method: Principal Component Factors. Rotation: orthogonal varimax. Number of observations: 9,089,457. Retained factors: 4.

Once the variables Electric Clothes Dryer, Electric Stove and Dehumidifier were eliminated from the sample, a second Principal Component Analysis was performed but this time excluding electricity consumption. Table 4.4 shows the obtained results from this analysis. As it was expected, Factor 1 is mainly associated with climate conditions (HI and Cooling Hours), Factor 2 with structural characteristics of the household (number of air conditioners, owning ceiling fans and the number of people living in the house) and Factor 3 with owning a Central Air Conditioner and a Programmable Thermostat.

Table **4-4**: Rotated factor loadings and unique variances.

Variable	Factor1	Factor2	Factor3	Uniqueness
HI	**0.9055**	-0.0002	-0.0001	0.1801
Cooling Hours	**0.9055**	-0.0004	-0.0004	0.1801
ACs	0.0000	**0.7901**	-0.2800	0.2974
CAC	-0.0008	-0.1600	**0.8292**	0.2869
PT	-0.0075	0.2108	**0.4573**	0.7464
CFs	0.0106	**0.4584**	**0.4219**	0.6118
People	-0.0034	**0.7437**	0.1074	0.4353

Notes: Factor Analysis Solution based on Polychoric Correlation Matrix. Method: Principal Component Factors. Rotation: orthogonal varimax. Number of observations: 9,136,260. Retained factors: 3.

From the results shown in Table 4.4, factor scores were estimated. The factor scores are defined as estimates of the underlying factor values for each observation. Since the factors are not observed, we must estimate them as functions of the observed variables. In this study, the regression method was applied (Thomas, 1951).

As it was previously stated, households were divided in six treatment groups; each group designated for a different pricing treatment during declared peak hours. Since the objective consist of analyzing whether the effect of these treatments differs based on the obtained factor values for each customer, it would be interesting to evaluate the characteristics of each group by means of the factor solution. In this way, the mean value of each standardized factor score by treatment group for the years 2012 and 2013 are shown in Figures 4.1 and 4.2, respectively. It must be noted that when the estimated factors are equal to zero, the values of the associated observed variables are equal to the sample mean. Thus, when a factor score is greater/less than zero, it means that the associated variables are greater/less than the sample mean.

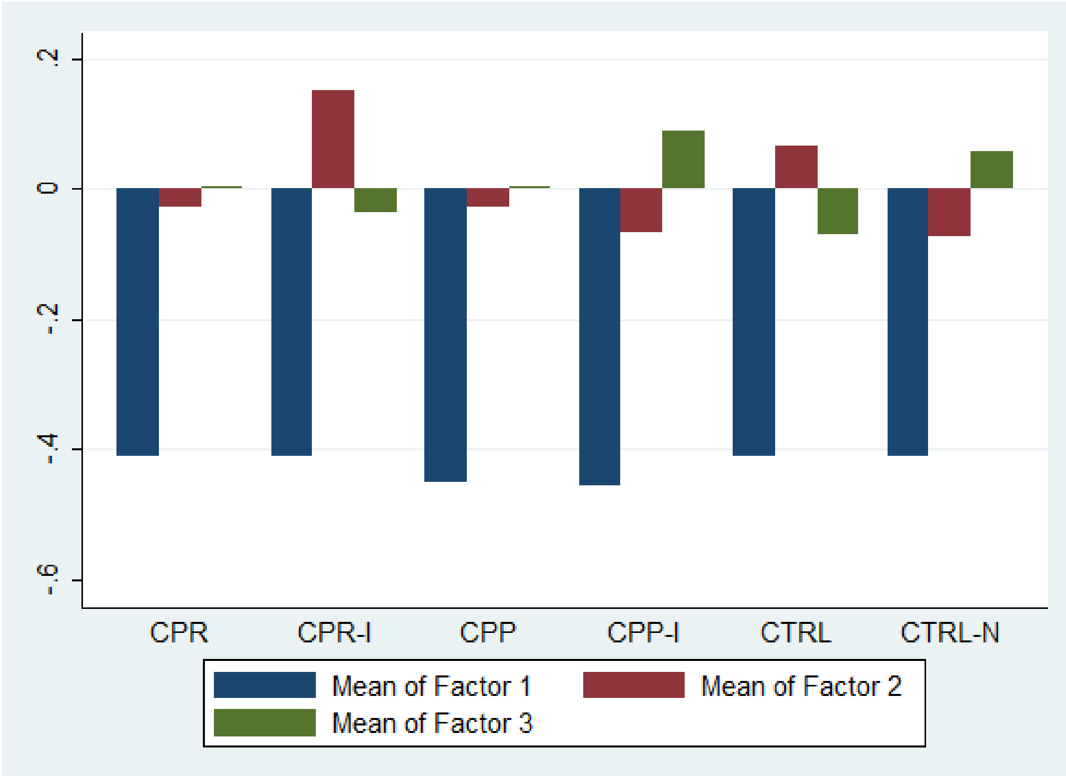

Figure **4-1**: Average Factor Scores by Treatment Group. Year 2012.

As it can be seen in Figure 4.1, Factor 1 takes negative values across treatment groups (naturally, the magnitude is relatively similar in all groups). This fact simply means that during 2012 the temperature and the apparent temperature were less than the average values for both years. On the contrary, Figure 4.2 shows that for 2013, the same variables were greater than the mean values.

Also, in order to correctly interpret both figures, it should be remembered that between 2012 and 2013 some customers decided to stop participating in the program and some others were transitioned to another treatment group as part of the program design.

The CPR group seems to be on average similar to the average household in the sample (Factor 2 and Factor 3 are almost zero) on both years. Customers on the CPR-I group have more Air Conditioners, more Ceiling Fans and their households are occupied by a greater number of people than the average household in the sample. Additionally, their houses seem to be on average not equipped with Central Air Conditioners and Programmable Thermostats. Meanwhile, the CPP-I group shows an opposite characterization to the CPR-I group (the mean of Factor 2 is less than zero and the mean of Factor 3 is greater than zero). To sum up, Figures 1 and 2 show that the groups are different based on socioeconomic characteristics, even when the program was implemented as a Randomized Control Trial.

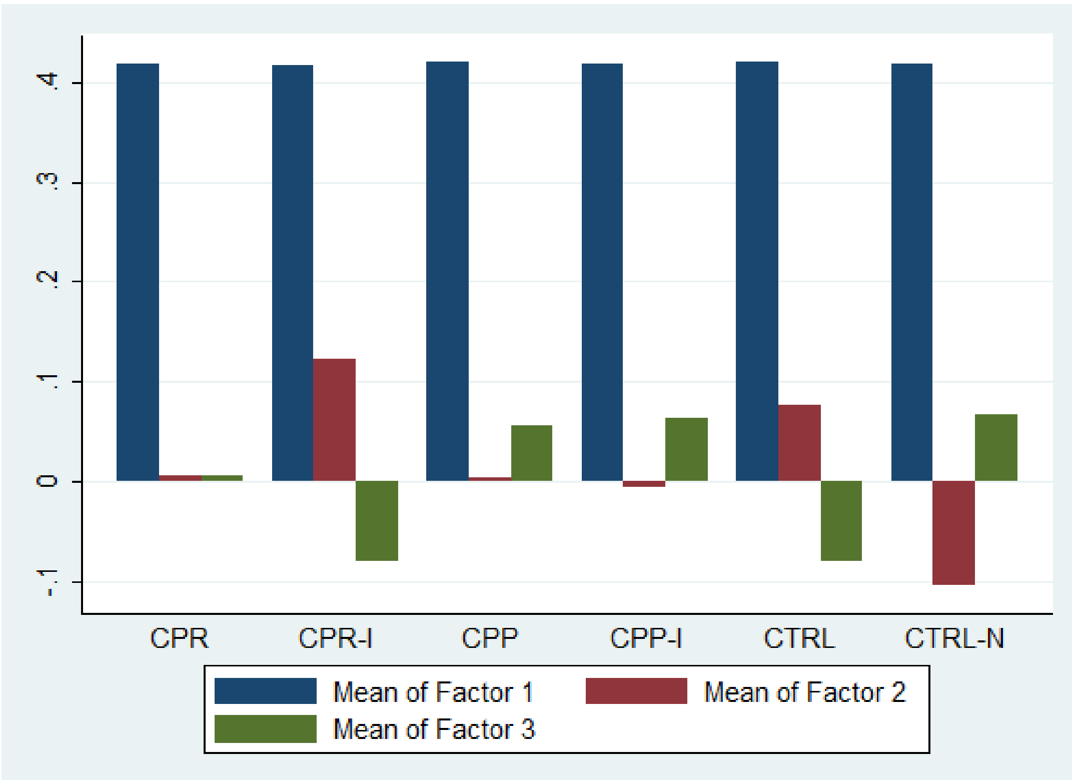

Figure **4-2**: Average Factor Scores by Treatment Group. Year 2013.

Methodology

In order to determine whether the effect of different pricing treatments during critical peak hours differs based on socioeconomic characteristics; this study proposes to include the factor solution from the previous analysis in a difference-in-difference regression model.

The proposed model takes the following form,

$$\mathrm{HourlyLoad}_{it} = \sum_{j=1}^{5} \beta_j(\mathrm{event}_t \times \mathrm{treatment}_{ji}) + \sum_{j=1}^{5}\sum_{m=1}^{3} \gamma_{jm}(\mathrm{event}_t \times \mathrm{treatment}_{ji} \times F_{mit})$$

$$+ \sum_{m=1}^{3} \delta_m(\mathrm{event}_t \times F_{mit}) + \sum_{j=1}^{5}\sum_{m=1}^{3} \alpha_{jm}(\mathrm{treatment}_{ji} \times F_{mit}) + \sum_{m=1}^{3} \theta_m F_{mit}$$

$$+ \rho(\mathrm{event}_t) + C_i + \varepsilon_{it} \qquad (1)$$

where Hourly Load_{it} is the hourly load for customer i for hour t, $\mathrm{treatment}_{ji}$ is a dummy variable that equals 1 if the customer i belongs to the treatment group j, event_t equals 1 for critical peak hours, F_{mit} is the estimated Factor m for customer i for hour t, C_i is a customer fixed effect, and ε_{it} is the error term.

The model presented is similar to a difference-in-difference-in-difference regression model in that it includes a triple-difference in order to assess the potential heterogeneity in the customer response based on different socioeconomic characteristics. However, it differs from the traditional triple-difference model since it allows for customer specific fixed effects which prevent the inclusion of time-invariant regressors.

The parameters β_j $(j = 1, \dots, 5)$ measure the treatment effect when all factors are equal to zero and the parameters γ_{jm} $(j = 1, \dots, 5; m = 1, \dots, 3)$ capture the treatment effect conditioned on the values of different factors.

Results

Results of the estimation of equation (1) are presented in Table 4.5. The table shows the estimated parameters corresponding to the interaction between $\mathrm{treatment}_{ji}$ and event_t (on bold letters) and the estimated parameters corresponding to each triple interaction. Clustered standard errors at the customer level are shown in parenthesis.

As it can be seen, results for year 2012 do not suggest the existence of heterogeneous effects based on socioeconomic and climate factors. None of the estimated parameters associated with the triple interaction terms are statistically significant at reasonable levels; except the one associated with Factor 2 in the CPP-I group. This last result suggests that higher values of Factor 2 (more air conditioners, ceiling fans and people living in the household) imply a greater response to treatment (i.e. a greater fall in electricity consumption during declared peak events). Besides, it must be noted that moderate amounts of heterogeneity cannot be detected given the imprecision of the estimates in column 1 of Table 4.5.

Using the sample of observations for the year 2013 (column 2 of Table 4.5), the existence of heterogeneous effects can be identified more precisely. First, as it was mentioned above, Factor 2 seems to be positively associated with a greater impact of treatment over electricity consumption. In other words, customers in the CPR, CPP-I or CTRL-N groups with higher values of Factor 2 consumed less electricity during declared peak hours, relative to customers in the control group with similar characteristics, than customers with lower values of Factor 2. A similar role seems to be play by Factor 1 (climate conditions) for some treatment groups; higher temperatures led to larger impacts of the CPP and CPP-I treatments. Finally, it is interesting to note that it is not possible to assess the existence of heterogeneous effects associated with different values of Factor 3.

When both periods are considered (column 3 of Table 4.5), the results are relatively similar to those obtained for the year 2013; the effect of some treatments is greater (lower consumption of electricity during declared peak hours) when the values of the variables associated with Factor 1 and Factor 2 are larger than the sample mean (i.e. the factor scores take positive values). Also, in this case, Factor 3 seems to be relevant for the CPR-I treatment; during declared peak hours, electricity consumption of those customers who have greater scores of

Factor 3 (associated with owning a Central Air Conditioner and a Programmable Thermostat) was lower, relative to comparable customers in the control group.

Further, it is interesting to note that when all factors are equal to zero (meaning that a household has the characteristics of the average household in the sample) the estimated effects of the different treatments are not statistically significant. Even when one should account for the imprecision of the estimates, this fact suggests that the previously estimated effects (without including the factor scores in the regression model) were driven by the behavior of customers whose households are different from the average household in the sample.

To further evaluate the existence of heterogeneous responses, Table 4.6 and Table 4.7 show the estimated parameters for each critical peak event. During 2012, as it was expected, the results are not stable over time. For example, only on the first event of the year, the CPR treatment shows a significant heterogeneity associated with Factor 2. Also, it can be seen that, during some critical peak events, the effects of the CPR-I and CPP treatments are lower when Factor 2 takes larger values (while, in some cases, the effect of the CPP-I treatment is increasing in Factor 2). These results are contrary to what was shown in Table 4.5 and suggest that the evidence of heterogeneous effects associated with Factor 2 would seem to be inconclusive.

During 2013 (Table 4.7), even when the results are not stable in terms of statistical significance, the heterogeneity associated with Factor 2 has a unique pattern. In other words, the evidence suggests that the impact of every treatment (except the CPP treatment) over electricity consumption is greater the larger the Factor 2.

Also, it is interesting to note that during the first critical peak event of 2013, Factor 1 played an opposite role to the one described previously; higher temperatures were associated with a lesser impact of treatment over electricity consumption. However, it can be seen that for other critical peak events the direction of this interaction is reversed.

Finally, the evidence of heterogeneity associated with Factor 3 is low and ambiguous. In some cases, it seems to reduce the impact of treatment and, in other cases it plays the opposite role.

To sum up, the results presented up to this point suggest that in general the effects of the different treatments analyzed in this study show some evidence of heterogeneity associated with Factor 2. In particular, households characterized by a greater value of this factor (due to a higher number of Air Conditioners, the existence of ceiling fans and a higher number of people living in the household) present a greater response to treatment, in the sense that they consume less electricity during declared peak hours, relative to customers in the control group with similar characteristics. Meanwhile, the potential heterogeneity associated with Factor 1 and 3 appears to be inconclusive.

Table **4-5**: Treatment effects and interactions terms.

	2012	2013	2012-2013
	(1)	(2)	(3)
CPR	**-0.0421**	**-0.00336**	**-0.0288**
	(0.0335)	(0.0588)	(0.0349)
Factor 1	-0.00927	-0.00688	-0.00710
	(0.0290)	(0.0218)	(0.0154)
Factor 2	-0.00353	-0.0869*	-0.0893**
	(0.0276)	(0.0525)	(0.0379)
Factor 3	0.0145	0.0626	0.0442
	(0.0552)	(0.0568)	(0.0395)
CPR-I	**-0.000427**	**0.0151**	**-0.0321**
	(0.0384)	(0.0742)	(0.0409)
Factor 1	-0.0398	-0.0295	-0.0102
	(0.0325)	(0.0271)	(0.0189)
Factor 2	0.0134	-0.0304	-0.0493
	(0.0299)	(0.0682)	(0.0473)
Factor 3	-0.0610	-0.120	-0.0839*
	(0.0629)	(0.0810)	(0.0497)
CPP	**-0.0525**	**0.00740**	**0.00584**
	(0.0365)	(0.0546)	(0.0381)
Factor 1	0.00495	-0.0362*	-0.0351**
	(0.0320)	(0.0213)	(0.0166)
Factor 2	0.0294	-0.0731	-0.0352
	(0.0354)	(0.0478)	(0.0388)
Factor 3	-0.0603	0.0237	0.00156
	(0.0550)	(0.0457)	(0.0337)
CPP-I	**-0.0700**	**0.0652**	**-0.00347**
	(0.0453)	(0.0592)	(0.0452)
Factor 1	-0.0360	-0.0749***	-0.0469***
	(0.0390)	(0.0218)	(0.0179)
Factor 2	-0.0723*	-0.155***	-0.104**
	(0.0420)	(0.0557)	(0.0460)
Factor 3	-0.0288	0.0492	0.0332
	(0.0609)	(0.0608)	(0.0498)
CTRL-N	**-0.0120**	**0.0236**	**0.0510**
	(0.0389)	(0.0533)	(0.0374)
Factor 1	0.0265	-0.0130	-0.0264*
	(0.0344)	(0.0198)	(0.0158)
Factor 2	-0.00984	-0.142***	-0.113***
	(0.0363)	(0.0485)	(0.0397)
Factor 3	-0.0266	0.0159	-0.00476
	(0.0558)	(0.0447)	(0.0326)
Observations	4,567,287	4,234,338	8,801,625

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012 and from May 2013 to September 2013. Customer fixed effects were included. Clustered standard errors at the customer level are in parenthesis.*** p<0.01, ** p<0.05, * p<0.1.

Table **4-6**: Treatment effects and interactions terms by event. Year 2012.

	2012 Events			
	(1)	(2)	(3)	(4)
CPR	**0.211**	**-0.00166**	**-0.0833***	**-0.0614**
	(0.197)	(0.0535)	(0.0440)	(0.0728)
Factor 1	-0.153	-0.00754	0.0967	0.00402
	(0.111)	(0.0708)	(0.162)	(0.0790)
Factor 2	-0.0828*	0.0289	0.0616	-0.0222
	(0.0467)	(0.0454)	(0.0429)	(0.0413)
Factor 3	0.0160	0.0509	-0.00341	-0.00555
	(0.0589)	(0.0885)	(0.0711)	(0.0544)
CPR-I	**-0.00193**	**0.0318**	**-0.0213**	**-0.0596**
	(0.220)	(0.0599)	(0.0491)	(0.0801)
Factor 1	-0.0458	-0.0504	-0.0859	0.0559
	(0.125)	(0.0774)	(0.182)	(0.0912)
Factor 2	-0.0398	0.0595	0.0789*	-0.0452
	(0.0479)	(0.0520)	(0.0472)	(0.0438)
Factor 3	-0.0275	-0.0738	-0.106	-0.0369
	(0.0643)	(0.0848)	(0.0730)	(0.0694)
CPP	**0.0996**	**-0.00790**	**-0.0637**	**-0.0823**
	(0.203)	(0.0522)	(0.0494)	(0.0738)
Factor 1	-0.0784	-0.0535	-0.0844	0.0548
	(0.114)	(0.0722)	(0.186)	(0.0820)
Factor 2	-0.0385	0.0822*	0.0962**	-0.0223
	(0.0571)	(0.0486)	(0.0475)	(0.0462)
Factor 3	-0.0920	-0.0392	-0.0634	-0.0463
	(0.0579)	(0.0768)	(0.0726)	(0.0544)
CPP-I	**0.335**	**-0.0688**	**-0.122****	**-0.127**
	(0.300)	(0.0675)	(0.0531)	(0.0779)
Factor 1	-0.274*	-0.0598	0.268	0.105
	(0.158)	(0.0759)	(0.235)	(0.0930)
Factor 2	-0.120*	-0.0641	0.0262	-0.134**
	(0.0677)	(0.0530)	(0.0525)	(0.0668)
Factor 3	0.000311	-0.0110	-0.0584	-0.0470
	(0.0773)	(0.0792)	(0.0807)	(0.0700)
CTRL-N	**0.108**	**0.0548**	**-0.0196**	**-0.0816**
	(0.229)	(0.0635)	(0.0515)	(0.0727)
Factor 1	-0.0331	-0.0555	0.0109	0.0905
	(0.130)	(0.0861)	(0.191)	(0.0822)
Factor 2	-0.00963	-0.0183	0.0306	-0.0423
	(0.0612)	(0.0524)	(0.0534)	(0.0488)
Factor 3	0.0155	-0.0542	-0.0456	-0.0225
	(0.0741)	(0.0767)	(0.0753)	(0.0565)
Obs.	4,567,287			

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012 and from May 2013 to September 2013. Customer fixed effects were included. Clustered standard errors at the customer level are in parenthesis.*** p<0.01, ** p<0.05, * p<0.1.

Table **4-7**: Treatment effects and interactions terms by event. Year 2013.

	2013 Events									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CPR	**-0.961****	**-0.239**	**0.321**	**0.160**	**-0.516**	**0.303**	**-0.00777**	**-0.211**	**0.204**	**-0.0904**
	(0.466)	(0.626)	(0.430)	(0.415)	(0.373)	(0.448)	(0.0596)	(0.366)	(0.207)	(0.377)
Factor 1	0.305*	0.0879	-0.102	-0.0604	0.161	-0.0967	0.0130	0.0546	-0.0892	0.0271
	(0.156)	(0.198)	(0.145)	(0.125)	(0.124)	(0.130)	(0.0846)	(0.155)	(0.0882)	(0.156)
Factor 2	-0.125	-0.0947	-0.123	-0.158*	-0.139*	-0.0936	-0.0104	-0.0406	-0.0629	-0.0235
	(0.0943)	(0.0817)	(0.0831)	(0.0879)	(0.0820)	(0.0873)	(0.0535)	(0.0677)	(0.0693)	(0.0712)
Factor 3	-0.123	0.0870	0.0815	0.111	0.226**	0.0706	0.0531	0.00632	0.0572	0.0595
	(0.0846)	(0.0993)	(0.105)	(0.0913)	(0.107)	(0.104)	(0.0374)	(0.0622)	(0.0549)	(0.0677)
CPR-I	**-1.421*****	**0.496**	**1.173***	**0.296**	**-0.682**	**0.438**	**0.0374**	**0.180**	**-0.0989**	**-0.151**
	(0.497)	(0.743)	(0.650)	(0.447)	(0.471)	(0.552)	(0.0689)	(0.383)	(0.252)	(0.465)
Factor 1	0.451***	-0.173	-0.421*	-0.127	0.230	-0.154	-0.0137	-0.119	0.00697	0.0363
	(0.166)	(0.232)	(0.220)	(0.136)	(0.157)	(0.161)	(0.0862)	(0.160)	(0.109)	(0.192)
Factor 2	0.0528	0.0101	-0.0875	-0.142	0.0126	-0.0223	0.116	-0.0722	-0.174**	0.00465
	(0.140)	(0.102)	(0.116)	(0.106)	(0.0974)	(0.0939)	(0.0883)	(0.0959)	(0.0806)	(0.0889)
Factor 3	-0.251*	-0.153	-0.178	-0.114	-0.0828	-0.197	-0.0374	-0.0939	0.0488	-0.143
	(0.151)	(0.139)	(0.134)	(0.140)	(0.133)	(0.140)	(0.102)	(0.108)	(0.0943)	(0.1000)
CPP	**-0.396**	**-0.148**	**0.433**	**0.301**	**-0.345**	**-0.0539**	**0.00940**	**0.186**	**0.212**	**0.223**
	(0.438)	(0.607)	(0.417)	(0.399)	(0.385)	(0.426)	(0.0548)	(0.335)	(0.200)	(0.362)
Factor 1	0.0917	0.0158	-0.178	-0.117	0.0842	-0.0163	-0.0382	-0.129	-0.126	-0.124
	(0.144)	(0.193)	(0.141)	(0.121)	(0.127)	(0.124)	(0.0773)	(0.141)	(0.0837)	(0.149)
Factor 2	-0.0889	-0.0958	-0.103	-0.123	-0.105	-0.0914	0.0299	-0.0700	-0.103	0.0180
	(0.0906)	(0.0691)	(0.0757)	(0.0832)	(0.0757)	(0.0797)	(0.0451)	(0.0645)	(0.0688)	(0.0600)
Factor 3	-0.0831	0.0626	-0.00805	0.0666	0.115	-0.0331	0.0981**	-0.0292	0.0817	-0.0280
	(0.0769)	(0.0597)	(0.0657)	(0.0784)	(0.0722)	(0.0725)	(0.0394)	(0.0573)	(0.0569)	(0.0595)
CPP-I	**-1.122****	**0.0948**	**0.156**	**0.577**	**-0.741***	**0.392**	**-0.00506**	**-0.0364**	**0.0634**	**-0.00926**
	(0.502)	(0.644)	(0.477)	(0.430)	(0.440)	(0.437)	(0.0677)	(0.382)	(0.231)	(0.416)
Factor 1	0.324*	-0.0656	-0.109	-0.238*	0.185	-0.184	-0.00357	-0.0241	-0.0361	-0.0511
	(0.167)	(0.204)	(0.163)	(0.131)	(0.146)	(0.127)	(0.0942)	(0.162)	(0.0962)	(0.172)
Factor 2	-0.108	-0.191**	-0.219***	-0.288***	-0.225***	-0.230***	-0.0380	-0.106	-0.111	-0.0379
	(0.0959)	(0.0843)	(0.0840)	(0.0877)	(0.0800)	(0.0875)	(0.0510)	(0.0691)	(0.0767)	(0.0679)
Factor 3	-0.0204	0.0496	-0.0117	0.0541	0.0962	-0.0422	0.0945	0.0276	0.0881	0.161
	(0.0826)	(0.0874)	(0.0707)	(0.0922)	(0.0813)	(0.0832)	(0.0661)	(0.0642)	(0.0598)	(0.104)
CTRL-N	**-1.087****	**-0.858**	**0.151**	**-0.123**	**-0.0105**	**-0.0301**	**-0.0467**	**0.0770**	**0.210**	**-0.439**
	(0.453)	(0.655)	(0.434)	(0.411)	(0.417)	(0.455)	(0.0547)	(0.363)	(0.207)	(0.372)
Factor 1	0.351**	0.267	-0.0661	0.0116	-0.00804	0.0169	0.0405	-0.0141	-0.0507	0.182
	(0.150)	(0.209)	(0.147)	(0.125)	(0.138)	(0.132)	(0.0807)	(0.153)	(0.0863)	(0.155)
Factor 2	-0.192**	-0.183**	-0.202**	-0.219**	-0.147*	-0.150*	-0.0147	-0.0770	-0.0956	-0.139**
	(0.0883)	(0.0723)	(0.0786)	(0.0889)	(0.0788)	(0.0830)	(0.0486)	(0.0661)	(0.0662)	(0.0603)
Factor 3	-0.113	0.0336	-0.0318	0.0303	0.105	-0.00147	0.0827**	0.00586	0.0254	0.0237
	(0.0826)	(0.0635)	(0.0644)	(0.0775)	(0.0734)	(0.0727)	(0.0354)	(0.0595)	(0.0519)	(0.0624)
Obs.	4,234,338									

Notes: Dependent variable: hourly load per customer. Least-squares dummy variable (LSDV) regressions. Periods: From August 2012 to December 2012 and from May 2013 to September 2013. Customer fixed effects were included. Clustered standard errors at the customer level are in parenthesis.*** p<0.01, ** p<0.05, * p<0.1.

Chapter 5

Survival Analysis of the GMP Consumer Behavior Study

Introduction

The successful implementation of Demand Response programs could result in lower peak demands allowing for lower system marginal prices, better infrastructure planning, and less system contingencies (Faruqui, 2006). However, in order to determine the feasibility of these studies, it is necessary to answer, among others, the following questions: 1) do customers respond to time-varying prices? 2) If yes, are those responses consistent across price changes? 3) What factors determine customers' responsiveness to time-varying prices? And 4) what determines attrition rates among customers participating in DR programs?

Using data from a pilot study carried out by Green Mountain Power (GMP) as a component of the eEnergy Vermont Smart Grid project in Rutland, VT, chapter 2 of this study found that the pricing structures associated with the CPR and CPR-I treatments do not seem to be effective at reducing electricity consumption during critical peak events. A similar conclusion can be made about the CTRL-N treatment. Unlike the latter treatments, CPP and CPP-I treatments seem to be effective. However, the magnitude of the responses to critical events for these treatment groups varies significantly across events and years. This later result represents a challenge for further penetration of DR programs due to the need for consistent response patterns.

Chapter 3 of this study seeks to obtain more information on the factors determining customer responsiveness to time-varying tariffs in order to gain a better understanding of the real potential of time-based demand response programs. The obtained results suggest that households with a higher number of air conditioners, ceiling fans, and people present a greater response to treatments.

The main objective of this chapter is to better understand attrition rates among customers participating in the Green Mountain Power (GMP) pilot study. In order to achieve this objective, I implemented a Survival Analysis model to a dataset of 16,545 households randomly divided into 8 groups, each of which was assigned a different treatment during declared peak hours.

Monthly observations of numerous covariates from March 2012 through September 2013 were used for the analysis. The covariates included in the analysis are: Treatment group, number of air conditioners in the household, number of people in the household, whether anyone in the household works full time for a pay, type of residence, ceiling fans ownership, electric clothes dryer ownership, electric stove ownership, dehumidifier ownership, central air conditioner ownership, programmable thermostat ownership, household ownership status (rented or owned), household income, education level, number of rooms and monthly load. These predictors include continuous, categorical and dichotomous variables. The first step of the analysis is to determine the particular influence of each variable on the survival of each household. This is done using the non-parametric log-rank test for categorical and dichotomous variables, and the univariate Cox proportional hazard model for the continuous variables. Then, statistically significant predictors are included in a multivariate Cox regression. Finally, statistically significant predictors resulting from the multivariate Cox regression are kept and iterations of these variables are included in the final regression. Results show that survival of customers depends on their Treatment Group and Income. In the case of the CPR-CPP and CPR-CPP-I groups being asked if they wanted to transition from the CPR to the CPP group appears to have had a great impact on survival rates.

From looking at the hazard ratios the model indicates that being enrolled in the Control+Notification treatment group increases the rate of desertion by 39% relative to the Control Group. Receiving the CPP treatment increases the rate of desertion by three times relative to the control group. Being enrolled in the CPP-I or CPR treatment groups increases the rate of desertion by 2 times. This rate is also increase by 2.4 by being enrolled in the CPR-I treatment. The desertion rate is increased by 8 times by being a part of the group CPR-CPP. Finally, the desertion rate is increased by 6 times by being enrolled in group CPR-CPP-I.

In the case of the income variable desertion rates are decrease by moving from income group 2 (100%-70.2% = 29.8%) to any of the other groups. With the highest reduction obtained by moving from group 1 to group 9 (100%-24.4%) =75.6%. Finally, asking a household if it wants to transition from the CPR to the CPP group through phone makes it 27% more likely to drop out.

Research Methodology

Duration, defined as the time elapsed until a certain event takes place is analyze using a survival analysis. In this study, I seek to analyze the duration of households in the GMP pilot program from March 2012 to September 2013. Distribution of customers across groups for 2012 and 2013 are shown in tables 5.1 and 5.2.

Table **5-1**: Distribution of customers across groups (2012).

	Month										
Group and Status	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	**Attrition Rate***
CPR	393	393	363	363	362	362	356	355	352	350	11%
CPR-I	204	204	204	204	203	203	188	188	187	187	8%
CPP	392	392	390	390	388	387	329	320	320	320	18%
CPP-I	195	195	195	195	195	195	158	154	153	153	22%
CPR-CPP	391	391	391	391	391	391	353	351	343	321	22%
CPR-CPP-I	195	195	195	195	195	195	172	172	172	172	4%
CTRL	398	397	396	394	392	386	388	386	383	382	4%
CTRL-N	397	397	393	393	393	393	384	383	383	383	8%
Total	2565	2564	2527	2525	2519	2512	2328	2309	2293	2268	12%

Only customers that accepted their treatment and remained on it and customers that decided to stop participating after being placed on their treatment status.
*Calculated from March to December 2012.

Table **5-2**: Distribution of customers across groups (2013).

	Month									
Group and Status	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	**Attrition Rate***
CPR	327	325	323	322	322	321	314	314	309	6%
CPR-I	180	174	174	174	174	173	170	167	167	7%
CPP	318	313	310	306	299	299	299	280	270	15%
CPP-I	153	141	140	139	139	139	134	134	132	14%
CPR-CPP	311	228	225	219	217	217	217	216	191	39%
CPR-CPP-I	162	135	125	117	112	105	105	105	104	36%
CTRL	383	383	383	381	376	369	369	369	368	4%
CTRL-N	383	382	382	379	379	376	374	372	371	3%
Total	2217	2081	2062	2037	2018	1999	1982	1957	1912	16%

Only customers that accepted their treatment and remained on it and customers that decided to stop participating after being placed on their treatment status.
*Calculated from January to September, 2013.

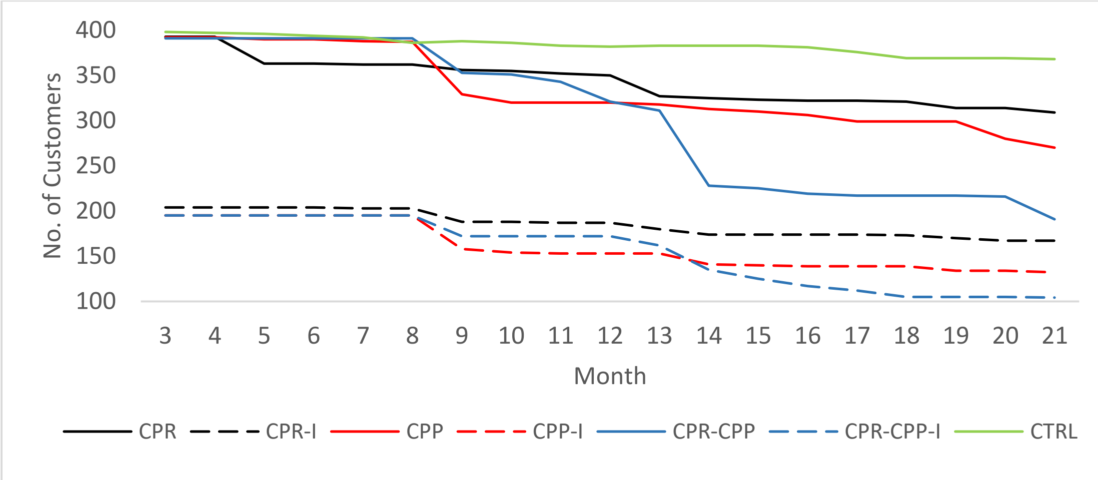

Figure **5-1**: Number of study participants remaining on their assigned rate vs. time.

There are several techniques available to estimate survival times, including non-parametric (e.g. Kaplan-Meier analysis), semi-parametric (e.g. Cox Regression) and parametric techniques (e.g. econometric regressions). Characteristics of survival analysis data, such as censoring and non-normality, make traditional techniques such as multiple linear regressions or ANOVA difficult to apply (Hosmer 1999). A censored observation is defined as an observation lost to follow up or drop out of the study, or if the study ends before the observation has an outcome of interest. There are four types of censoring in survival analysis: 1) Right Censoring: subject leaves the study before an event occurs, or the study ends before the event occurred. 2) Left Censoring: subject experiences the event of interest before enrollment. 3) Right truncation: the entire study population has already experience the event of interest. 4) Left truncation: subject have been at risk before entering the study (Klein 2005). The data use in this analysis only has right censoring. Some households left the study before its conclusion and others stay until it was finished.

Parametric techniques model the underlying survival function assuming that the dependent variable (time-to-event) takes a known distribution (e.g. Weibull, exponential, or lognormal) an estimates the parameters of these distributions. Semi-parametric regressions model the effect of predictors on the hazard rate but leaves the baseline hazard rate unspecified. In doing so only relative risk is estimated. Non-parametric techniques make no mathematical assumptions computing the empirical probability of surviving past certain times in the sample.

In this study I will use the test of equality across strata to explore whether or not to include a predictor in the final model. For the categorical variables I will use the log-rank test of equality across strata which is a non-parametric test. For the continuous variables I will use a univariate Cox proportional hazard regression (Cox 1972) which is a semi-parametric model.

The hazard function plays a very important role in survival analysis. The Cox proportional hazards model investigates the relationship of predictors and the time-to-event through the hazard function. It assumes that the predictors have a multiplicative effect on the hazard and that this effect is constant over time.

The hazard function is the probability that an individual will experience an event within a specific time interval and can be interpreted as the risk of experiencing the specific event at time t.

The hazard function – denoted by $h(t)$ – can be estimated using the following equation:

$$h(t) = \frac{\begin{array}{c} number\ of\ individuals\ experiencing \\ an\ event\ in\ interval\ beginning\ at\ t \end{array}}{\begin{array}{c} (number\ of\ individuals\ surviving\ at\ time\ t)x \\ (interval\ width) \end{array}} \quad (5.1)$$

Mathematically, the hazard function can be expressed as:

$$h(t) = h_o e^{\beta_1 x_1 + \cdots + \beta_n x_n} \quad (5.2)$$

Where $h(t)$ is the hazard function at time t, $h_o(t)$ is the base rate hazard function, $x_1 +\cdots +x_n$ are predictor variables, and the regression coefficients to be estimated from the data $\beta_1,\cdots ,\beta_n$.

The interpretation of the Cox model is done using hazard ratios (HR), defined as the ratio of the predicted hazard function under two different values of a predicted variable.

$$HR = \frac{h_1(t)}{h_2(t)} = \frac{h_o e^{\beta x_1}}{h_o e^{\beta x_2}} = e^{\beta(x_1 - x_2)} \quad (5.3)$$

A hazard ratio greater than 1 indicates a covariate that is positively associated with the event probability, a ratio less than one indicates an event is less likely to occur, and a hazard ratio of 1 indicate the predictor has no effect on the hazard of the event.

Since the Cox model is built on the assumption that hazards are proportional between the values of the predictors, this condition must be satisfied by the model in order to obtain valid results (Cleves 2008).

There are several approximations to test the proportionality assumptions. The plot of the Schoenfeld residuals vs time can be used for continuous predictors. A horizontal line in the graphs indicates no violation of the proportionality condition. The comparison of the log-log transformation of the Kaplan-Meier survival curves is use for categorical predictors. Parallel curves that not intersect after time apart indicates no violation of the proportionality assumption (George et al 2014). Another form of checking for proportionality is to perform a test of proportional hazards assumption which uses the Schoenfeld and scaled Schoenfeld residuals. If any of the covariates are significant then those predictors are not proportional (Hosmer 1999). The later method is used in this study.

Survival Analysis

The objective of this analysis is to model time until drop-out of the Green Mountain Power (GMP) pilot study for households enrolled in 7 different treatment groups. The variable timefailure contains time until drop-out and the variable dropout indicates whether the household drops (dropout=1) or remains in the study (dropout=0).

Univariate Analysis

The first step of the analysis is to run a test of equality across strata to explore whether or not to include the predictor in the final model. For the categorical variables I will use the log-rank test while for the continuous variables I will use a univariate Cox proportional hazard regression. This elimination scheme is implemented because all predictors in the dataset are variables that could be relevant to the model. Results of the log-rank test of equality across strata for all predictors are shown in table 3. Non-statistically significant predictors at least at the 10% level will be excluded from the final model.

Table **5-3**: Univariate test for all predictors.

Variable	Mean	Std. Dev.	Min	Max	P-Value
Group	4.52	2.49	1	8	0.00
Airconditioners	1.81	0.96	1	5	0.26
PPl	1.98	0.78	1	5	0.03
Work Full Time	0.58	0.49	0	1	0.04
Type of Residence	4.62	1.00	1	7	0.00
Cillness	0.22	0.41	0	1	0.32
Ceiling Fans	0.67	0.46	0	1	0.04
Electric Clothes Dryer	0.82	0.37	0	1	0.01
Electric Stove	0.71	0.45	0	1	0.62
Dehumidifier	0.37	0.48	0	1	0.10
Central Air Conditioner	0.04	0.20	0	1	0.45
Programable Thermostat	0.43	0.49	0	1	0.61
Rent or Own	0.90	0.29	0	1	0.00
Income	4.67	1.92	1	9	0.00
Education	4.67	1.62	1	7	0.93
Rooms	2.35	0.91	1	4	0.01
Notify by Phone	0.27	0.44	0	1	0.00
Notify by Text	0.03	0.17	0	1	0.74
Notify by Email	0.026	0.15	0	1	0.29
Notify by IHD	0.021	0.14	0	1	0.05
Monthly Load	506.79	419.52	0	6250.78	0.00

Model Building

For model building I will consider all statistically significant predictors at the 10% level. Results of the Cox regression for the proposed model are shown in table 5.4.

Table **5-4**: Cox estimation model.

Variable	**Hazards ratio**	**P-value**	**Variable**	**Hazards ratio**	**P-value**
Treatment Group			ceilingfans	0.893	0.390
1	1.393	0.343	electric clothes dryer	1.196	0.298
2	3.477	0.000	Dehumidifier	0.837	0.216
3	1.808	0.114	rooms		
4	1.798	0.075	2	1.023	0.904
5	2.346	0.019	3	1.293	0.301
6	7.749	0.000	4	1.228	0.470
7	6.119	0.000	Income		
Number of People in HH			2	0.810	0.389
2	0.978	0.898	3	0.519	0.012
3	1.150	0.540	4	0.371	0.001
4	1.119	0.645	5	0.386	0.000
5	1.198	0.591	6	0.489	0.018
6	2.074	0.062	7	0.300	0.054
7	0.394	0.411	8	0.389	0.014
8	4.755	0.043	9	0.253	0.024
9	0.010	0.000	phone	1.385	0.013
Work full time	1.169	0.310	IHD	0.804	0.641
Type of residence			monthly load	0.999	0.139
2	1.090	0.806			
3	0.792	0.477			
6	0.896	0.856			
7	0.962	0.969			

Predictors number of people, work full time, type of residence, ceiling fans, electric clothes dryer, dehumidifier, number of rooms, IHD notification, and monthly load are not significant and are dropped from the model. Results for the obtained model are shown in table 5.5.

Table **5-5**: Cox regression for Group, household ownership and income.

Variable	**Coef.**	**P-value**	**Variable**	**Coef.**	**P-value**
Treatment Group			Income		
2	0.245	0.422	2	-0.209	0.393
3	0.579	0.018	3	-0.606	0.020
4	-0.012	0.970	4	-0.954	0.001
5	1.451	0.000	5	-0.894	0.000
6	1.178	0.000	6	-0.677	0.020
7	-0.065	0.055	7	-0.626	0.066
8	-0.309	0.301	8	-0.811	0.016
rent or own	-0.772	0.000	9	-1.017	0.042
Phone	0.287	0.026			

It can be observed in table 5.5 that the covariates Group, rentorown, income and phone are all statistically significant. Now I will consider interactions.

Interactions

There is a potential relationship between Income, household ownership status and acceptance of a given treatment. For this reason, all the considered interactions could be statistically significant. The obtained results are shown in table 5.6.

Table **5-6**: Interaction terms.

Variable	**Hazard Rate**	**P-value**
Treatment Group/rent or own		
2	1.403	0.606
3	1.683	0.323
Treatment Group/Income		
2-2	1.521	0.687
2-3	1.291	0.813
Income/rent or own		
2	1.125	0.762
3	0.612	0.227

It can be observed from table 5.6 that none of the interaction terms are statistically significant. Thus, they will not be included in the final model.

Proportionality Assumption

One of the main assumptions of the Cox proportional hazard model is proportionality. In order to test for this condition, I use the Schoenfeld and scaled Schoenfeld residuals. If the test is not significant then the proportionality cannot be rejected and it can be assumed that there is no a violation of the proportionality assumption (Hosmer 1999). The obtained test of proportional hazards assumption for covariates Group, rentorown, Income and Phone is shown in table 5.7.

Table **5-7**: Test of proportional hazards assumption for Group, rentorown and Income.

Variable	**rho**	**chi2**	**df**	**Prob>chi2**
Group	-0.066	1.14	1	0.285
rentorown	-0.163	6.95	1	0.008
Income	-0.054	0.01	1	0.922
Phone	-0.098	2.41		0.120
Global Test		13.61	4	0.008

The test of proportional hazards for the variable *rentorown* is statistically significant then the hypothesis of no violation of the proportionality assumption cannot be rejected. Thus, the covariate is dropped from the final model. Table 5.8 shows the test of proportional hazards for *Group*, *income* and *phone*. Since the test is no statistically significant proportionality cannot be rejected and it is assumed that there is no a violation of the proportionality assumption.

Table **5-8**: Test of proportional hazards assumption for *Group*, *Income* and *Phone*.

Variable	**rho**	**chi2**	**df**	**Prob>chi2**
Group	-0.070	1.27	1	0.260
Income	-0.054	1.00	1	0.317
Phone	-0.111	3.14	1	0.046
Global Test		2.96	2	0.112

Results of the Cox regression for the final model are shown in table 5.9. From looking at the hazard ratios the model indicates that being enrolled in the Control+Notification treatment group increases the rate of desertion by 39% relative to the Control Group. Receiving the CPP treatment increases the rate of desertion by three times relative to the control group. Being enrolled in the CPP-I or CPR treatment groups increases the rate of desertion by 2 times. This rate is also increase by 2.4 by being enrolled in the CPR-I treatment. The desertion rate is increased by 8 times by being a part of the group CPR-CPP. Finally, the desertion rate is increased by 6 times by being enrolled in group CPR-CPP-I.

In the case of the income variable desertion rates are decrease by moving from income group 2 (100%-70.2% = 29.8%) to any of the other groups. With the highest reduction obtained by moving from group 1 to group 9 (100%-24.4%) =75.6%. Finally, asking a household if it wants to transition from the CPR to the CPP group through phone makes it 27% more likely to drop out.

Table **5-9**: Cox regression for Group and income.

Variable	**Hazards ratio**	**P-value**
Treatment Group		
1 (CTRL-N)	1.391	0.060
2 (CPP)	3.436	0.000
3 (CPP-I)	2.035	0.072
4 (CPR)	1.965	0.046
5 (CPR-I)	2.455	0.014
6 (CPR-CPP)	8.279	0.000
7 (CPR-CPP-I)	6.146	0.000
Income		
2	0.702	0.143
3	0.433	0.001
4	0.383	0.000
5	0.361	0.000
6	0.348	0.000
7	0.294	0.002
8	0.280	0.000
9	0.244	0.004
Phone	1.271	0.063

Discussion

Results of the performed Survival Analysis suggest that attrition rates vary significantly across treatment groups. Attempting to change customers from the CPR to CPP treatment group appears to have a dramatic effect on drop-out rates. However, providing households with an in-home display reduces by two times the risk of dropping out when facing the possibility of transitioning from a CPR to a CPP tariff. Receiving and in-home display also had a significant effect on households enrolled in the CPP group. The obtained hazard rate for the CPP-I group are 100% smaller than that of the CPP group. This effect is not evident for the CPR group. Households in the CPR-I group have a hazard rate 0.4 times higher than that of households in the CPR group. Additionally, the obtained evidence suggest that high income households are less likely to drop-out than low income ones. Finally, asking a household if it wants to transition from the CPR to the CPP group through phone makes it 27% more likely to drop out.

Chapter 6

Supply Chain Model for a Vertically Integrated Oil Company: The Ecopetrol Case

Introduction

The oil supply chain is a complex process formed by three segments. Up, Mid and Downstream. The Upstream segment is made up by exploration and production and its main objectives are to find and produce oil, respectively. The midstream sector is made up by transportation facilities. Its objective is to evacuate oil and provide products to demand centers. Finally, the downstream segment is made up of refineries and petrochemical plants and its objective is to transform crude oil into oil derivatives such as jet fuel, diesel and gasoline. The operational planning of these three segments present various challenges. The production segment´s objective is to produce crude oil at the lowest possible cost, thus, low transport tariffs are a part of its objective function. Contrary to this, the transport segment´s objective is to transport crudes and products at the highest tariffs, thus, its objective is to charge the production segment with the highest possible rate. On the other hand, the refining segment´s objective is to produce oil derivatives at the lowest cost and sell them at the highest possible cost, thus, this segment wants cheap crude oil in order to obtain high refining margins.

As a consequence, in order to optimize profits of a vertically integrated oil company it is necessary to account for the conflicting interests among sectors by maximizing the company's overall utility and not the utility of each segment separately.

The objective of this work is to build a logistics model that integrates the production, transport and refining segments in order to maximize the utility of a vertically integrated oil company. In the process of maximizing the company's utility, the model enables a series of management decisions like: the use of multimodal transportation (i.e. trucks, pipes and vessels), production levels, transportation routes and infrastructure unavailability due to terrorist attacks or other events.

In order to carry out the stated objective, a network of production, transport and refining nodes was modeled. In addition to the production and transportation facilities, the model considers production volumes per field, transport costs per pipeline or truck, royalties and crudes and products prices.

Literature Review

In spite of the importance that the oil industry plays in the global economy it still manages its different segments as complete different entities. Therefore, relatively few attempts have been made at the development of systematic methods for efficiently managing the petroleum supply chain (Forrest and Oettli 2003). Several studies have addressed the modeling of Oil Field Development. These studies are mainly focus on the categories of investment planning, facility location and production planning. Goel and Grossmann (2004) implemented a stochastic programming model to optimize investment and operation in a multi-site oilfield under uncertainty in the size of the reservoirs. Gupta and Grossmann (2012) used a multi-period non-convex MINLP model for offshore oilfields development and planning. The model includes variables such as production rates, number of wells and storage. Crude Oil Transportation has also been modeled by several authors. These studies can be divided into three categories: crude oil transportation coupled with oilfield development (Aboudi et al. 1989), crude oil transportation coupled with refining (Rocha et al. 2009, Neiro and Pinto 2004) and crude oil transportation alone (Ribas et al 2010). Aboudi et al. (1989) develop a mixed-integer programming model for the planning of crude oilfield development and transport systems. Neiro and Pinto (2004) develop an integrated MINLP model for the refinery supply chain. In this study the network system is made up of a set of crude oil suppliers, refineries, and distribution centers. Al-Othman et al. (2008) extended the work of Neiro and Pinto (2004) by integrating petrochemicals into the model. Alabi and Castro (2009) use a large-scale linear programming model to optimize a refinery supply chain consisting of a horizontally integrated supply chain from crude oil supply to distribution. Fernandes et al. (2013) proposed a deterministic multi-entity, multi-echelon, multi-product and multi-transportation mixed integer linear program (MILP) that determines optimal depot locations, capacities, transportation modes, routes and networks affectations for long term planning of a downstream petroleum supply chain. Using a two-stage stochastic model, a robust min-max model and a max-min model, Ribas et al (2010) develop a planning tool that considered different transportation modes as well as the opportunity of investment at the transport nodes in order to expand capacity. Rocha et al. (2009) proposed a Mixed-Integer Linear Programming model that incorporates transportation modes, corresponding capacity, and class of ships for transferring crude oil from platforms to refineries in an integrated petroleum company. Chen et al. (2010) implement a Genetic Algorithm (GA) programming model to minimize logistics costs of importing crude oil. The model incorporates source nodes, transportation arcs and oil terminal ports of imported crude oil. In the refining segment, studies have been mainly focus at the modeling of uncertainty in spot selling prices, spot supply costs, and product demand (Escudero et al. 1999, Dempster et al. 2000, Li et al. 2004). Product blending and processing operations have been modeled using MINLP models by Neiro and Pinto (2004), Elkamel et al. (2008) and Kim et al. (2008). Integrated Supply Chain Models that include crude oil supply, transformation (refining), and distribution have also been developed. Kuo and Chang (2008) implemented a MILP model that incorporates maritime transportation, refinery planning, and distribution of products with multi-modal transport (pipelines and trucks) for the optimization of inventory levels, operation mode of each unit, and purchase of intermediate oils in petrochemical industries. Escudero et al. (1999) implemented a LP model to optimize a supply, transformation and distribution network consisting of tank storages, transforming sites, transshipment nodes, and destination depots.

This work adds to the existing literature by developing a model that maximizes the utility of a vertically integrated oil company including multimodal transportation, subsidiaries, financial metrics, transportation routes and infrastructure unavailability due to terrorist attacks or other reasons.

Petroleum supply chain

A supply chain can be defined as an integrated network of processes whose objectives are to procure, transform, distribute and sell finished products (Sahebi et al. 2014). Supply chain planning is generally divided into three categories depending on the time frame: strategic, tactical, and operational. Strategic planning has to do with long term planning and determines the structure of the supply chain. Decisions taken at this level involve capital expenditures (Capex). Tactical planning is related to the assignment of production targets and its associated logistics. These decisions impact medium term planning and usually involve operational expenditures (Opex). Finally, operational planning has to do with month to month decisions and determine the assignment of task to units at each facility (Maravelias and Sung, 2009). An integrated management of the supply chain is critical to reducing the propagation of undesirable events throughout the network and its importance is highlighted by the fact that companies can save up to 10% in operative costs by applying strategic and tactical supply chain models (Goetschalckx et al. 2002). In the specific case of the petroleum supply chain, it is formed by three segments: upstream, midstream, and downstream (see figure 6.1). The industry starts with exploration rights, continues with production and transport, and finishes with refining and commercialization of crude oil and products. Upstream activities include exploration, development, and production. After exploration is performed and reserves are incorporated, oil wells are drilled and oil is extracted. Crude oil that is produced must be transported from the wellhead to the refineries and ports via pipeline, trucks or vessels. Once crude blends reach the refinery they are converted into a variety of products including gasoline, diesel fuel, jet fuel, fuel oil and coke. Products are sold directly to large users, such as utilities and commercial customers both in local and international markets.

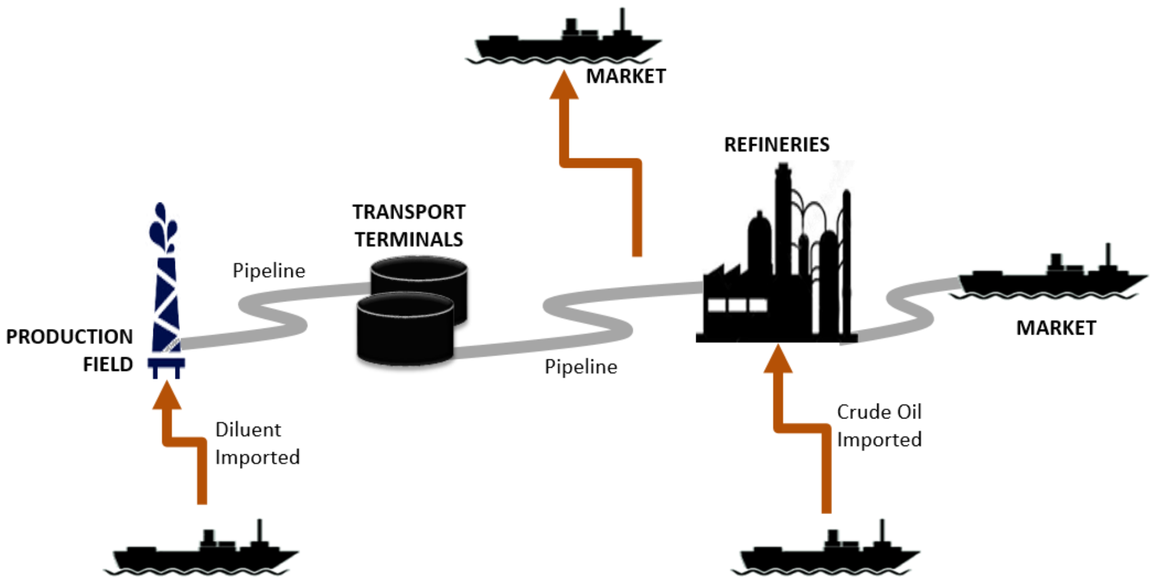

Figure **6-1**: Petroleum supply chain.

Production levels per well depend on the international price of crude and costs associated with lifting and transport of crude oil. Electricity and capital depreciation makes up most of the cost associated with pipeline transport while fuel cost makes up most of the cost associated with trucks and vessels transport. Refining margins depend on the international price of oil products and the price of crude oil. End products depend heavily on the refinery feedstock which is defined according to the configuration of the refinery.

This chapter is organized as follows: Section 6.4 describes the problem. Section 6.5 presents the proposed model. I then present a case study in Section 6.6, and close the chapter with some concluding remarks in Section 6.7.

Problem statement

The proposed model maximizes the utility of an integrated oil company accounting for the optimization of transportation routes for both crude and oil derivatives, multimodal transportation and refinery feedstock. Decisions to be made include the use of multimodal transportation (i.e. trucks and pipelines), transportation routes, product distribution plan and terrorist attacks management.

The overall optimization problem can be stated as follows:

Given

- production levels for each crude oil;
- oil derivatives demand and markets;
- fixed and variable costs for each production, transportation and refining node;
- international price for each crude oil and oil derivative;
- availability of each transportation node;
- tariffs at each transportation node;
- alternative transportation at each node;

Find

- optimum evacuation route and transportation mode for each case taking into account the risk associated with terrorist attacks and other infrastructure damage.

The result of the model provides potential solutions to be used by the decision-maker in order to generate the best operating plan according to her/his preferences.

Mathematical model

This section presents the mathematical model of the petroleum supply chain.

Indices

$i = Index\ of\ production, transport\ or\ refinery; i \in I$

$p = Index\ of\ products\ (crude\ oil, crude\ oil\ blends, gas, jet); p \in P$

$r = Index\ of\ transportation\ modes; r \in R; 1 = pipeline, 2 = truck, 3 = vessel$

$k = Index\ of\ customers\ (demand\ nodes); k \in K$

$i = i'\ Alias$

$h = infrastructure\ availability\ scenarios$

Parameters

$D_{kp} = Demand\ for\ product\ p\ at\ demand\ node\ k$

$P_i = Production\ of\ crude\ oil\ at\ node\ i$

$R_i = Production\ of\ oil\ products\ at\ node\ i$

$S_{ii',h} = Capacity\ of\ production, transport\ or\ refinery$

$f_{ip} = Production\ cost\ of\ product\ p\ at\ node\ i$

$r_{ip} = Refining\ cost\ of\ product\ p\ at\ node\ i$

$Y_{ii'pr} = Crude\ oil\ or\ product\ p\ shipped\ from\ node\ i\ to\ node\ i'via\ transportation\ mode\ r$

$C_{ii'pr} = Tariff\ per\ unit\ of\ product\ p\ shipped\ from\ node\ i\ to\ node\ i'via\ transportation\ mode\ r$

$O_{ii'pr} = Operating\ cost\ per\ unit\ of\ product\ p\ from\ node\ i\ to\ node\ i'via\ transportation\ mode\ r$

$M_{ii'pr} = Selling\ price\ per\ unit\ of\ product\ p\ from\ node\ i\ to\ node\ \ i'\ via\ transportation\ mode\ r$

$B_{ii'pr} = Buying\ price\ per\ unit\ of\ product\ p\ from\ node\ i\ to\ node\ \ i'\ via\ transportation\ mode\ r$

$\overline{TOPQ}_{ii'r} = Take\ or\ pay\ contract\ \ for\ segment\ i - i'with\ mode\ r$

$TOPT_{ii'r} = Take\ or\ pay\ tariff\ for\ segment\ i - i'with\ mode\ r$

$SAPT_{ii'r} = Ship\ and\ pay\ tariff\ for\ segment\ i -\ i'\ with\ mode\ r$

$\theta_h = Scenario\ probability$

$\alpha = CVaR\ confidence\ interval$

Decision Variables

$SAPQ_{ii'pr} = Ship\ and\ pay\ quantity\ for\ segment\ i -\ i'\ with\ mode\ r$

$TOPQ_{ii'r} = Take\ or\ pay\ quantity\ \ for\ segment\ i - i'with\ mode\ r$

$CVaR = Conditional\ Value\ at\ Risk$

$E_{ii'pr} = Product\ sold\ from\ node\ i\ to\ node\ i'via\ transportation\ mode\ r$

$IMP_{ii'pr} = Crude\ oil\ or\ product\ imported\ from\ node\ i\ to\ node\ i'via\ transportation\ mode\ r$

$w_h = values\ that\ exceed\ CVar$

$AFFILIATE\ DIVIDENDS = dividents\ received\ for\ infrastructure\ ownership\ stakes$

Objective function for a vertically integrated oil company accounting for risk associate to infrastructure damage is given by:

$$xOBJ = \sum_{n}\sum_{c} M_{ii'pr} \cdot E_{ii'pr}$$
$$- \sum_{n}\sum_{c} B_{ii'pr} \cdot IMP_{ii'pr} - \sum_{n}\sum_{c}\left[P_i f_{ip} + R_i r_{ip} + O_{ii'pr} \cdot Y_{ii'pr}\right]$$
$$+ AFFILIATE\ DIVIDENDS - CVaR \quad (6.1)$$

$$s.t.$$

$$Y_{ii'pr} \leq S_{ii',h}$$
$$Y_{ii'pr} = refinery\ demand + vol\ exported$$
$$AFFILIATE\ DIVIDENDS = Y_{ii'pr} \cdot Node\ Ownership\ Stake$$
$$SAPQ_{ii'pr} + TOPQ_{ii'pr} + P_i = D_{kp} + SAPQ_{i'ipr} + TOPQ_{i'ipr} + IMP_{ii'pr} - demand\ breach$$
$$TOPQ_{ii'pr} = \overline{TOPQ}_{ii'r} - contractual\ breach_h$$
$$SAPQ_{ii'pr} + TOPQ_{ii'pr} \leq S_{ii',h}$$
$$w_h \geq contractual\ breach(h) - CVaR$$
$$CVaR = \frac{1}{(1-\alpha)}\sum_{h}\theta_h \cdot w_h$$
$$w_h, CVaR \geq 0$$

Equation 6.1 maximizes the profit function for a vertically integrated oil company accounting for the risk associated to infrastructure damage. The first term represents revenues from crude oil and oil products sold. The second term represents cost of imported crude or products. The third term represents operating and production costs. The fourth term represents dividends received for partial ownership of transportation systems. The fifth term is the conditional value at risk. The first constraint limits the amount of crude oil production to the capacity of the field. The second constraint limits the amount of crude oil shipped to the refinery and transportation systems. The third term represents the dividends received due to ownership stakes in the infrastructure. The fourth constraint ensures that demand for crude oil and oil products is satisfied. The fifth term accounts for the volume committed in take or pay contracts. The final constrains are used to compute the conditional value at risk.

Case Study: Operational Planning at the Colombian National Oil Company (Ecopetrol)

Ecopetrol is a vertically integrated oil & gas company with activities ranging from petroleum and gas exploration to refining and distribution. The logistics activity at Ecopetrol is made up of three faces. The first one consist of generating production curves for each well. The second is the allocation of crude oil either to export or to refineries. Finally, evacuation plans are designed for each crude. Since in the transport process crudes are mixed, what reaches the refineries and export markets are crude blends. Ecopetrol has two main blends, Castilla and Vasconia. The percentage of crude oil production that goes into each blend depends on how the evacuation logistics is designed. Up to now, no efficient tool is available to model the entire petroleum supply chain at Ecopetrol. The proposed model aims to solve this problem by maximizing the overall utility of the company.

The model considered in this work partially represents the real-world petroleum supply chain planning problem of Ecopetrol. Ecopetrol has over 200 on-shore production fields, 2 refineries located at the northeast (GRB) and Caribbean Coast (GRB) of Colombia and a 5,000 km pipeline network. GRB (250,000 Barrels per Day –KBPD-) a medium conversion refinery has traditionally supply the local oil derivatives market while GRC (150KBPD) a high conversion refinery has the capacity to supply both local and international markets. Refineries and the export ports (Coveñas and Tumaco) are supplied with petroleum by three main pipeline branches (see figure 6.2). The OCENSA segment (capacity of 400,000 Barrels) which goes from the center of the country to the Caribbean coast by the east mountain range, the BICENTENARIO segment (200,000 Barrels) which goes from the center of the country to the Caribbean Coast by the west mountain range, and the OTA segment (capacity of 45,000 Barrels) which goes from the Colombian Amazon region to the Pacific Coast.

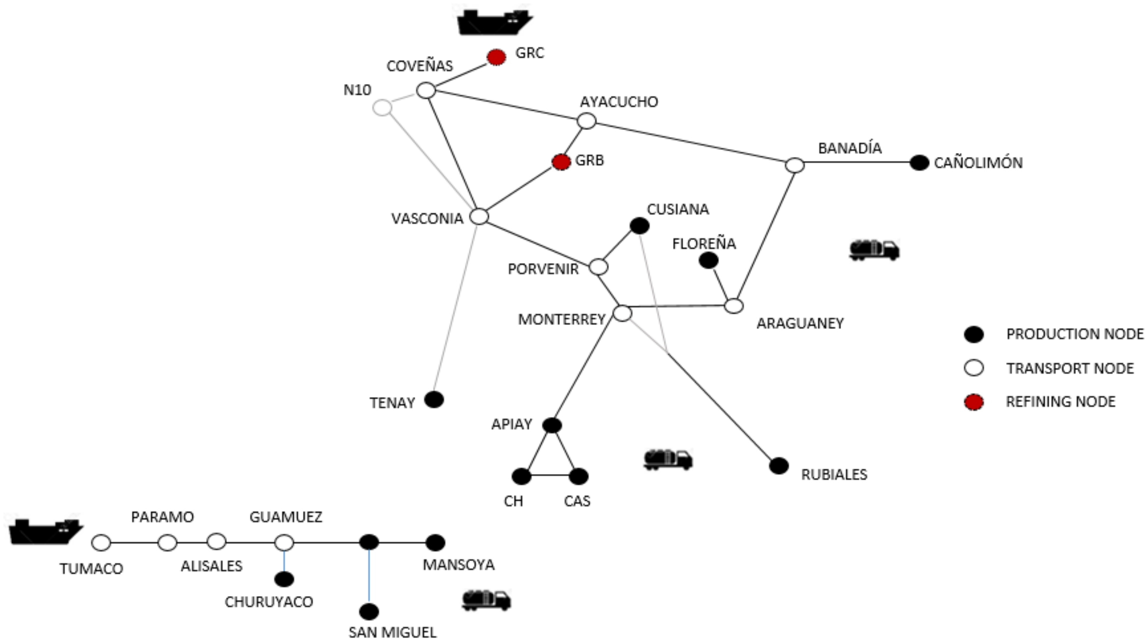

Figure **6-2**: Ecopetrol's simplified pipeline topology.

Fifty hundred and forty-seven petroleum types are considered to supply the complex. Petroleum types from different oil fields and with different properties are mixed at the transport segments resulting in different oil blends for export and refineries. 10 oil types are potentially supplied to GRC, 2 oil types can be send to GRB and 5 blends can be exported.

Case study: Bicentenario (BIC) and Ocensa (OCS) segments

Fifty percent of Ecopetrol's crude oil production comes from oil fields located in the Orinoquia region. There are two transport sub-systems built to take these crudes to the refineries and the export port of Coveñas. These sub-systems are the Ocensa segment (400,000 barrels) which goes from the center of the country to the Caribbean coast by the east mountain range and the Bicentenario segment (200,000 barrels) which goes from the center of the country to the Caribbean Coast by the west mountain range (see figure 3).

The decision of evacuating crudes using one segment or the other has several operational and financial implications. Evacuating crudes using the Bicentenario segment results in a higher quality oil blend sold at a better discount with respect to international prices. However, this segment has higher transport tariff and its functionality is constantly interrupted by terrorist attacks. On the other hand, the Ocensa segment has lower transport tariffs and a safer operation. However, the oil blend resulting from evacuating oil crudes using this route has a lower quality with a value, on average, four dollars below that of the oil blend obtained in the Bicentenario segment. Additionally, Ecopetrol has ownership stakes in both systems. This adds to the decision variables to take into account when deciding what system to use at a given time.

In terms of tariffs regimes, the Ocensa segment has a ship and pay structure with and average tariffs of $3.48 USD/Bl while the Bicentenario segment has both a ship and pay tariff of 6.40 USD/Bl and a ship or pay tariff of 8.54 USD/Bl. Tariffs for both systems are shown in table 6-1.

Table **6-1**: Tariff structure for Bicentenario (BIC) and Ocensa (OCS).

		BIC	OCS
Pipeline tariff (USD/bl)	SoP	8,54	-
	S&P	6,40	3,48

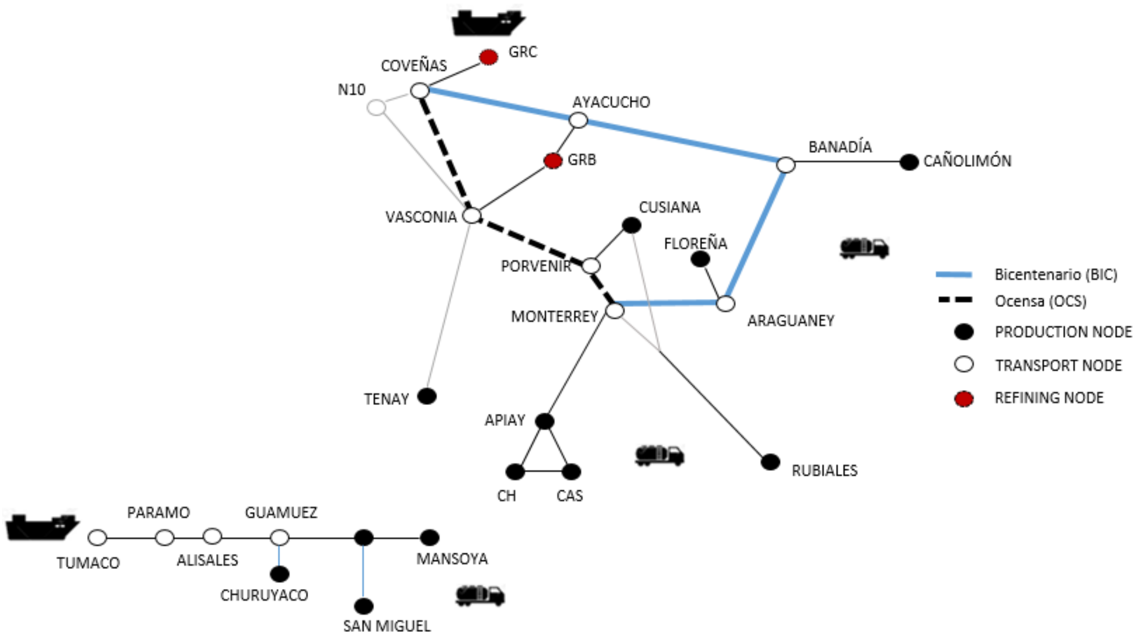

Figure **6-3**: BIC and OCS simplified pipeline topology.

The availability of the pipeline segments plays a central role when optimizing the profit of Ecopetrol. Some segments of the pipeline network suffer constant terrorist attacks. In 2014, the transport infrastructure was attacked 279 times (see figure 6.4). In addition to negative environmental, social and economic effects, these attacks change the configuration of the network by changing the availability of transport nodes. Scenarios of interruptions in the functionality of the transport system are modeled in the next session.

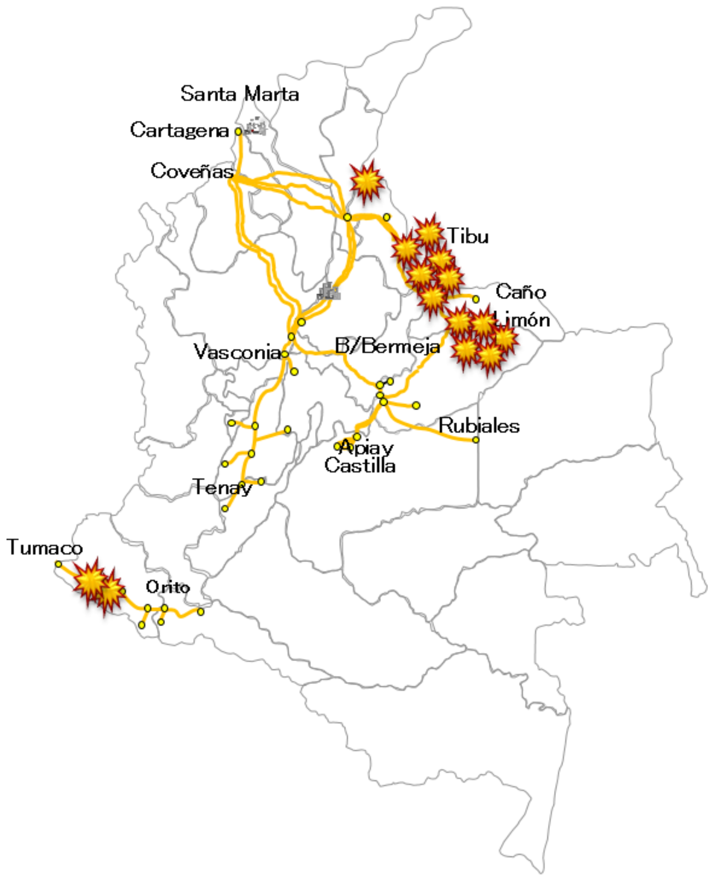

Figure **6-4**: Attacks to pipelines (2015:80, 2016:95, 2017:104).

Results

In this section, four different scenarios for the BIC and OCS systems are analyzed. The first scenario represents the base case and maximizes the utility function of the production, transport and refining segments assuming the above mentioned transport tariffs no terrorist attacks and no alternative transport. Results are presented in figure 6.5. Scenario 2 depicts the impact that the non-availability of different segments of the transport network have over the profit of the integrated oil company when no alternative transport mean is available. The third scenario maximizes the utility function of the production, transport and refining segments assuming the above mentioned transport tariffs for pipelines and an alternative transport mean tariff given by: $truck\ unitary\ cost \cdot (truck\ availability \cdot 20\% + truck\ dispatch \cdot 80\%)$ and terrorist attacks affecting the segment Banadia-Ayacucho with a descending probability distribution function. Scenario 4 maximizes the utility function of the production, transport and refining segments assuming the above mentioned transport tariffs for pipelines and an alternative transport mean tariff given by: $truck\ unitary\ cost \cdot (truck\ availability \cdot 20\% + truck\ dispatch \cdot 80\%)$ and terrorist attacks affecting the segment Banadia-Ayacucho with an increasing probability distribution function. Scenarios are run using equation 6.1. The obtained results for scenario 1 (base case) are presented in figure 6.5.

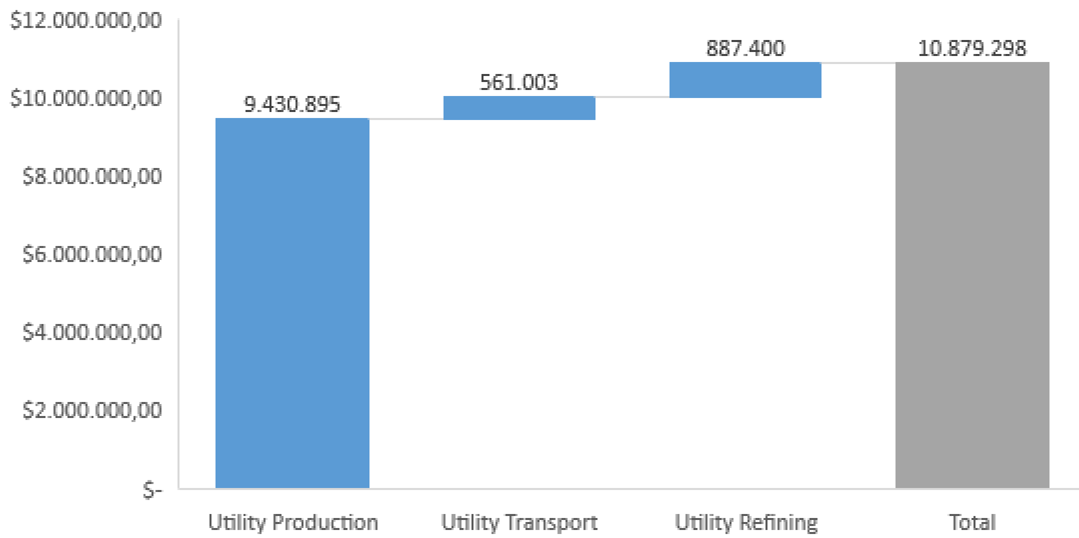

Figure **6-5**: Base case: Operational margin by segment (USD per day).

Scenarios assume the production of 590,226 bls/day of crude oil from which 564,226 bls/day are sent to international markets and 26,000 bls are sent to refineries. Additionally, a Brent price of $50 per barrel is assumed. A total utility of $10.8 MUSD is obtained with the production segment representing 86.7% of that value. The refining segment follows with 8.2% of the group's profits and the transport segment makes up the additional 5.1%. From these figures it can be inferred that at a per barrel measure, the production segment is the most profitable of the three segments, generating, on average, $16/barrel while the transport segment is the less profitable with $0.95/barrel. It is worth nothing that this exercise does not include the crude production costs (drilling, lifting, etc).

Scenario 2 depicts the impact that non-availability of the different segments of the transport network have over the profit of the integrated oil company when no alternative transport mean is available. The obtained results for scenario 2 are presented in figure 6.7.

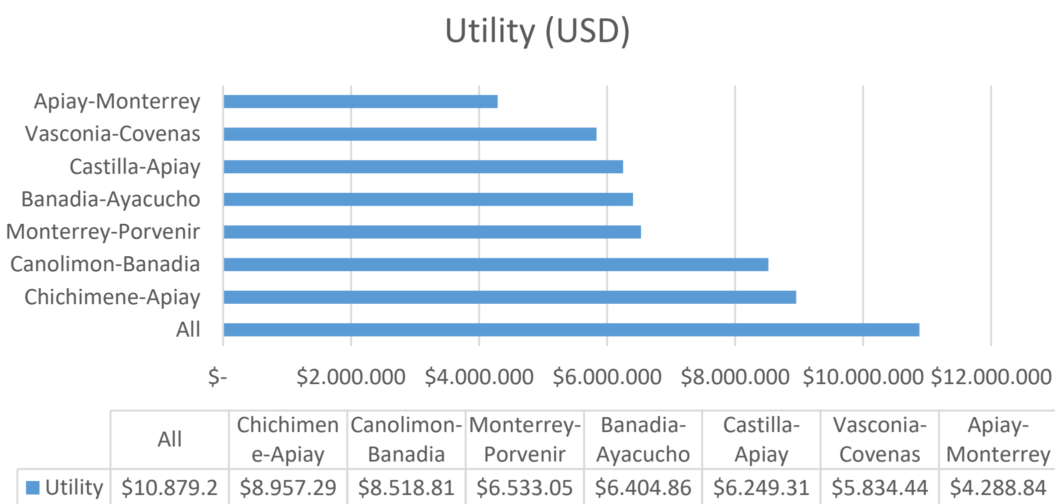

Figure **6-6**: Effect of non-availability of pipeline segments due to terrorist attacks or other events (USD per day).

It can be observed from figure 6.7 that an attack to the segment Apiay-Monterrey has the greatest impact on the company's profit (-37%) while the smaller impact is obtained when the segment Canolimon-Banadia is unavailable (-6.6%). In spite of having the smaller impact on the company's profit, the link Canolimon-Banadia has the highest number of terrorist attacks of the last 4 years. This segment has received, on average, 30 attacks per year with an average production loss of 7000 barrels of crude oil per day. The fact that the node with the lowest impact is the most attacked indicates that the attacker is not seeking to maximize the impact on the oil infrastructure but to generate social unrest, environmental impacts and political pressure.

Scenario 3 maximizes the utility function of the production, transport and refining segments assuming the above mentioned transport tariffs for pipelines and an alternative transport mean tariff given by: $truck\ unitary\ cost \cdot (truck\ availability \cdot 20\% + truck\ dispatch \cdot 80\%)$ and terrorist attacks affecting the segment Banadia-Ayacucho with a decreasing probability distribution function with 4 data points and a range of 0 to 1. The first point on the curve is 0 with a cumulative descending probability of 0.9 (10% of the distribution values are less than or equal to 1, 90% are greater). The second point on the curve is 0.2 with a cumulative descending probability 0.8 (20% of the distribution values are less than or equal to 0.8, 80% are greater). The third point on the curve is 0,8 with a cumulative descending probability of 0.3 (70% of the distribution values are less than or equal to 0.3, 30% are greater). The fourth point on the curve is 1 with a cumulative descending probability of 0.1. The obtained probability function is presented in figure 6.7.

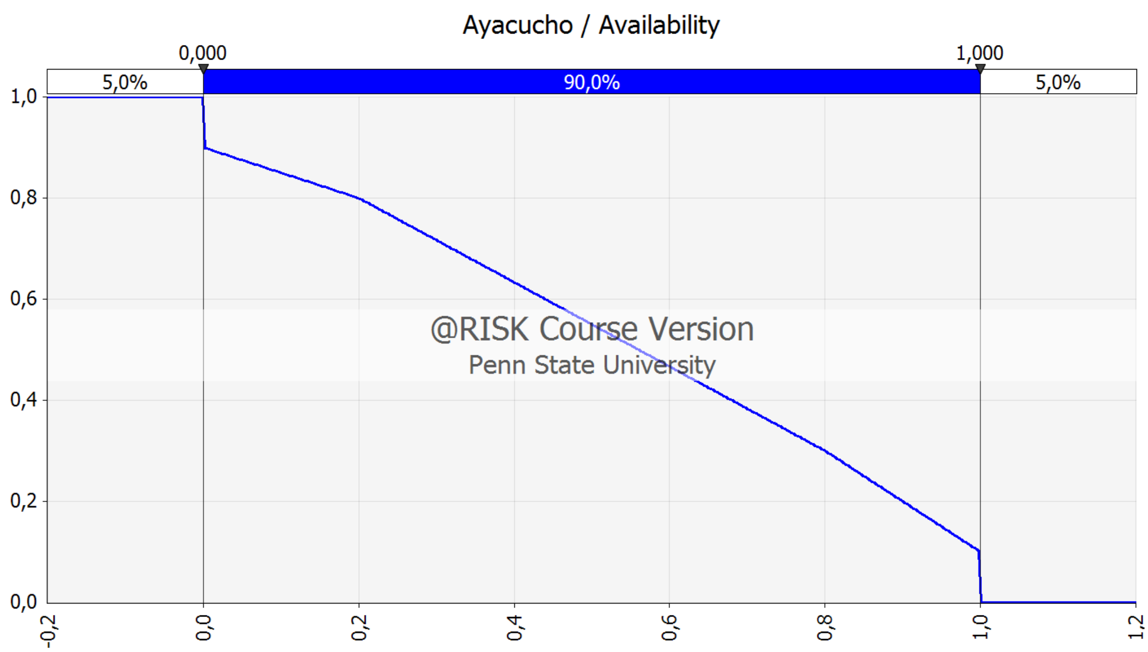

Figure **6-7**: Cumulative descending probability function in the Banadia-Ayacucho segment.

The tradeoffs for different alternative transport availability levels versus expected utility for the cumulative descending probability function describe above is presented in figure 6.8. It can be inferred from figure 6.8 that, in this scenario, paying for a 100% availability of the alternative transport mean results in an expected utility of $7.069.439 with a value at risk of $2.145.334 while no having any transport mean available results in an expected utility of $8.792.953 with a value at risk of $4.193.588. The final operational point depends on the risk profile of the decision maker.

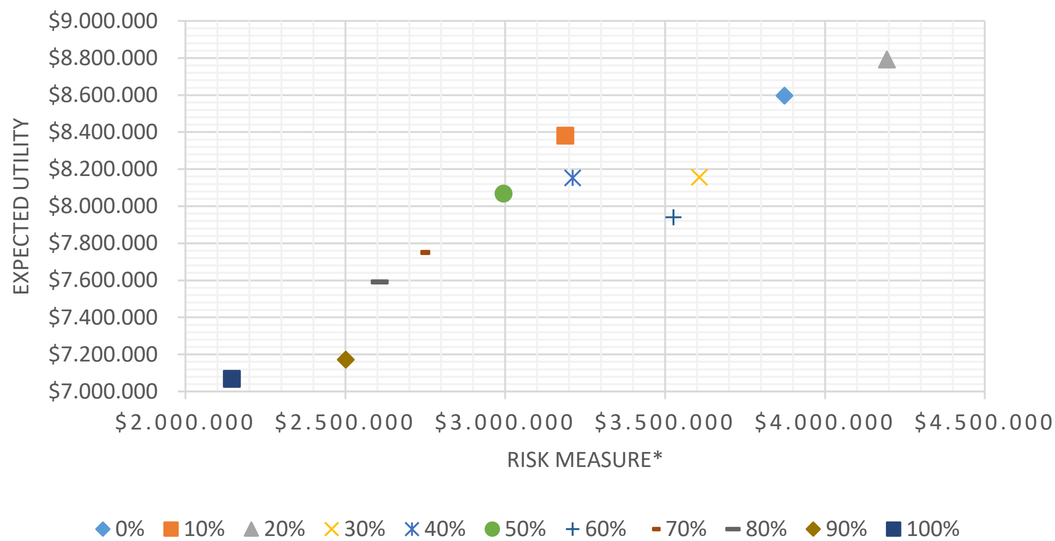

Figure **6-8**: Utility for different levels of incorporation of alternative transport mean (trucks) in the Banadia-Ayacucho segment with a descending probability distribution function.

*Risk Measure=Expected Utility-CVaR.

Scenario 4 maximizes the utility function of the production, transport and refining segments assuming the above mentioned transport tariffs for pipelines and an alternative transport mean tariff given by: $truck\ unitary\ cost \cdot (truck\ availability \cdot 20\% + truck\ dispatch \cdot 80\%)$ and terrorist attacks affecting the segment Banadia-Ayacucho with an increasing probability distribution function with 4 data points and a range of 0 to 1. The first point on the curve is 0 with a cumulative probability of 0.1 (10% of the distribution values are less than or equal to 0, 90% are greater). The second point on the curve is 0.2 with a cumulative probability 0.3 (30% of the distribution values are less than or equal to 0.2, 70% are greater). The third point on the curve is 0.8 with a cumulative probability of 0.8 (80% of the distribution values are less than or equal to 0.8, 20% are greater). The fourth point on the curve is 1 with a cumulative probability of 0.9. The obtained probability function is presented in figure 6.9.

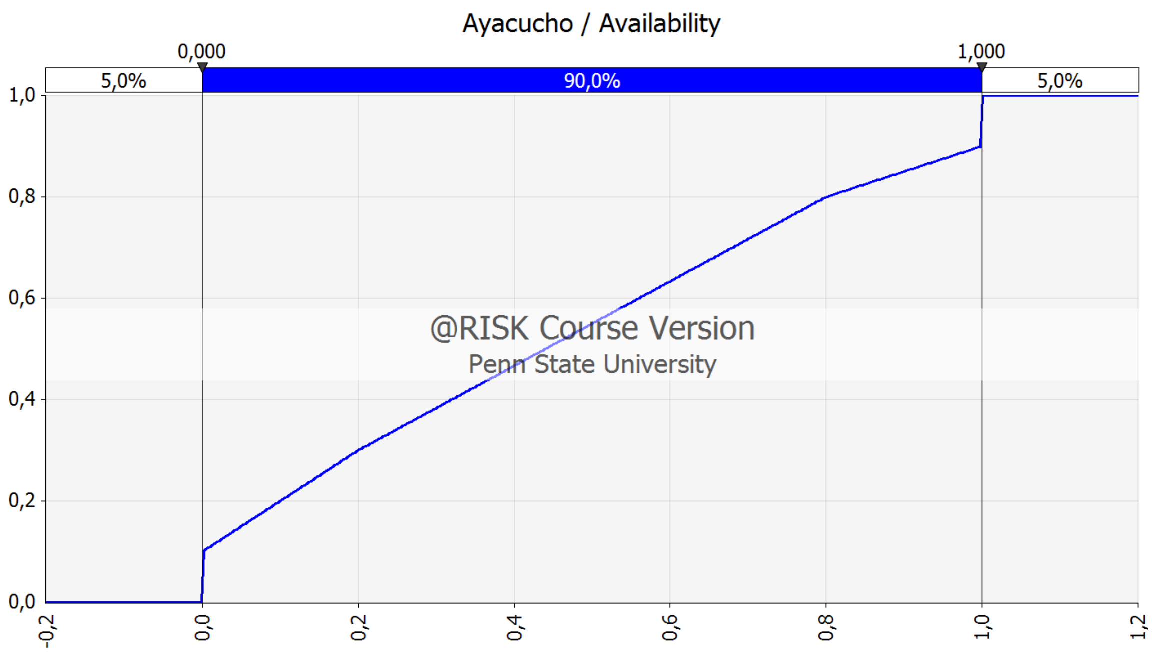

Figure **6-9**: Increasing probability function in the Banadia-Ayacucho segment.

The tradeoffs for different alternative transport availability levels versus expected utility for the increasing probability function described above is presented in figure 6.10. It can be inferred from figure 6.10 that, in this scenario, paying for a 100% availability of the alternative transport mean results in an expected utility of $6.768.966 with a value at risk of $2.562.802 while no having any transport mean available results in an expected utility of $7.931.544 with a value at risk of $3.314.002. The final operational point depends on the risk profile of the decision maker. However, it can be observed from figures 6.8 and 6.10 that as the probability of having a pipeline availability smaller than one increases the range of the value at risk increases.

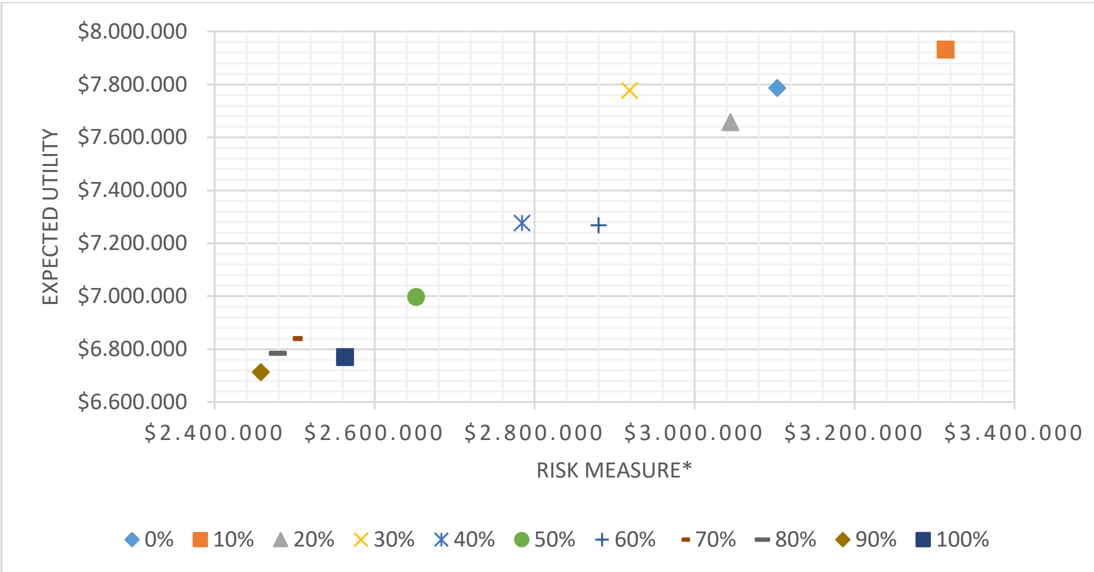

Figure **6-10**: Utility for different levels of incorporation of alternative transport mean (trucks) in the segment Banadia-Ayacucho with an increasing probability distribution function.

* Risk Measure=Expected Utility-CVaR.

Discussion and Conclusions

The supply chain topology is built through nodes representing pipelines, production fields and refineries. The case study showed how an integrated oil company can be modeled based on a general representation. Results of the analyzed scenarios have demonstrated the potential application of the model to real-world petroleum supply chains and how it can help decision maker in the planning process.

According to the presented results, planning the supply chain in an integrated manner makes it easier to understand the key drivers of the supply chain performance. For instance, it was shown how terrorist attacks have negative impacts of magnitudes depending on the affected node. In the analyzed case it could be observed how, according to historical data, attackers did not maximize the negative impact on the company's profits, but instead were centered on a specific node maybe due to geographical, environmental or political reasons.

In terms of alternative transport means (trucks), it was shown how having multimode transportation in scenarios of operational contingencies can ameliorate the negative effect of a terrorist attack on the company's profits. Using the CVaR as a measure of risk it was shown how the decision maker can choose an operational point according to its risk profile and the modeled probability distribution function for the availability of the pipelines.

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