CONSORTIUM FOR ELECTRIC RELIABILITY TECHNOLOGY SOLUTIONS

CALIFORNIA ENERGY COMMISSION

Customer Response to Day-ahead Wholesale Market Electricity Prices: Case Study of RTP Program Experience in New York

CONSULTANT REPORT

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Arnold Schwarzenegger, Governor

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PREFACE

The U.S. electric power system is in the midst of a fundamental transition from a centrally planned and utility-controlled structure to one that will depend on competitive market forces for investment, operations, and reliability management. Electric system operators are being challenged to maintain reliability levels needed for the digital economy in the face of changing industry structure and evolving market rules. The economic growth of the Nation is tied ever closer to the availability of reliable electric service. New technologies are needed to prevent major grid outages as experienced in the Western grid on August 10, 1996, which left 12 million customers without electricity for up to 8 hours and cost an estimated $2 billion.

The Consortium for Electric Reliability Technology Solutions (CERTS) was formed in 1999 to research, develop, and disseminate new methods, tools, and technologies to protect and enhance the reliability of the U.S. electric power system in the transition to a competitive electricity market structure.

CERTS is conducting public-interest electricity reliability research in four areas:

- Real-Time Grid Operations and Reliability Management
- Reliability and Markets
- Distributed Energy Resources Integration
- Reliability Technology Issues and Needs Assessment

What follows is the final report for the **Work for Others Contract No. 150-99-003** conducted by the Consortium for Electric Reliability Technology Solutions. The report is entitled **Customer Response to Day-ahead Wholesale Market Electricity Prices: Case Study of RTP Program experience in New York**. This project contributes to **Real-Time Grid Operations and Reliability Management Area** program.
For more information on the PIER Program, please visit the Energy Commission's Web site http://www.energy.ca.gov/pier/reports.html or contract the Energy Commission's Publications Unit at (916) 654-5200.

ABSTRACT

There is growing interest in policies, programs and tariffs that encourage customer loads to provide demand response (DR) to help discipline wholesale electricity markets. Proposals at the retail level range from eliminating fixed rate tariffs as the default service for some or all customer groups to reinstituting utility-sponsored load management programs with market-based inducements to curtail. Alternative rate designs include time-of-use (TOU), day-ahead real-time pricing (RTP), critical peak pricing, and even pricing usage at real-time market balancing prices. Some Independent System Operators (ISOs) have implemented their own DR programs whereby load curtailment capabilities are treated as a system resource and are paid an equivalent value. The resulting load reductions from these tariffs and programs provide a variety of benefits, including limiting the ability of suppliers to increase spot and long-term market-clearing prices above competitive levels (Neenan et al, 2002; Borenstein, 2002; Ruff, 2002).

Unfortunately, there is little information in the public domain to characterize and quantify how customers actually respond to these alternative dynamic pricing schemes. A few empirical studies of large customer RTP response have shown modest results for most customers, with a few very price-responsive customers providing most of the aggregate response (Herriges et al, 1993; Schwarz et al, 2002). However, these studies examined response to voluntary, two-part RTP programs implemented by utilities in states without retail competition.1 Furthermore, the researchers had limited information on customer characteristics so they were unable to identify the drivers to price response. In the absence of a compelling characterization of why customers join RTP programs and how they respond to prices, many initiatives to modernize retail electricity rates seem to be stymied.

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Disclaimer

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Final Report

Prepared for
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We would like to thank the following individuals and organizations without whose assistance this study would have been impossible: Peter Zschokke of National Grid, Catherine McDonough and Art Hamlin of Niagara Mohawk Power Corporation (NMPC), the New York Independent System Operator (NYISO), New York State Energy Research and Development Authority (NYSERDA), the New York Public Service Commission (NYPSC), and the SC-3A customers that voluntarily participated in this study.

We also thank our peer reviewers, Peter Schwarz (University of North Carolina), Steve Braithwait (Christensen Associates) and Joe Eto (LBNL), the members of our Technical Advisory Committee, Severin Borenstein and Jim Bushnell (University of California Energy Institute), Dick Schuler and Tim Mount (Cornell University) and Mike Jaske (CEC), and the members of our Stakeholder Advisory Committee, Bruce Kaneshiro (CPUC), Scott Cauchois (California Office of Ratepayer Advocates), Mike Jaske (CEC), Glen Perez (CAISO), Andrew Bell and Dewey Seeto (PG&E), Mark Wallenrod (SCE), Suzie Sides and Paul Borkovich (SDG&E), Barbara Barkovich (CLECA), Karen Lindh (CMA), Joe Desmond (Silicon Valley Manufacturers Association), Clyde Murley (BOMA), Jim Gallagher and Doug Lutzy (NYPSC), Dave Coup and Peter Douglas (NYSERDA), Dave Lawrence and Aaron Breidenbaugh (NYISO), Catherine McDonough and Arthur Hamlin (NMPC), Larry Dewitt (Pace University), and Bob Loughney (Multiple Interveners) for their input, suggestions and comments.

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List of Acronyms

CAC	Commodity Adjustment Charge
CBL	Customer Baseline Load
CES	Constant Elasticity of Substitution
CTC	Competition Transition Surcharge
DADRP	Day Ahead Demand Response Program
DAM	Day-Ahead Market
DR	Demand Response
DSM	Demand-Side Management
EDRP	Emergency Demand Response Program
EIS	Energy Information System
EMCS	Energy Management Control System
ESCo	Energy Service Company
HIPP	Hourly Integrated Pricing Program
ICAP/SCR	Installed Capacity/Special Case Resources (Program)
ISO	Independent System Operator
LBMP	Locational-Based Marginal Pricing
LBNL	Lawrence Berkeley National Laboratory
LRC	Load Resource Characterization
LSE	Load Serving Entity
NMPC	Niagara Mohawk Power Corporation
NYISO	New York Independent System Operator
NYPSC	New York Public Service Commission
NYSERDA	New York State Energy Research and Development Agency
RTP	Real-Time Pricing
SC-3A	NMPC's Large General Electric Service (TOU) Tariff
THI	Temperature Heat Index
VIPP	Variable Interruptible Pricing Program

Executive Summary

Overview

There is growing interest in policies, programs and tariffs that encourage customer loads to provide demand response (DR) to help discipline wholesale electricity markets. Proposals at the retail level range from eliminating fixed rate tariffs as the default service for some or all customer groups to reinstituting utility-sponsored load management programs with market-based inducements to curtail. Alternative rate designs include time-of-use (TOU), day-ahead real-time pricing (RTP), critical peak pricing, and even pricing usage at real-time market balancing prices. Some Independent System Operators (ISOs) have implemented their own DR programs whereby load curtailment capabilities are treated as a system resource and are paid an equivalent value. The resulting load reductions from these tariffs and programs provide a variety of benefits, including limiting the ability of suppliers to increase spot and long-term market-clearing prices above competitive levels (Neenan et al, 2002; Borenstein, 2002; Ruff, 2002).

Unfortunately, there is little information in the public domain to characterize and quantify how customers actually respond to these alternative dynamic pricing schemes. A few empirical studies of large customer RTP response have shown modest results for most customers, with a few very price-responsive customers providing most of the aggregate response (Herriges et al, 1993; Schwarz et al, 2002). However, these studies examined response to voluntary, two-part RTP programs implemented by utilities in states without retail competition.[1] Furthermore, the researchers had limited information on customer characteristics so they were unable to identify the drivers to price response. In the absence of a compelling characterization of why customers join RTP programs and how they respond to prices, many initiatives to modernize retail electricity rates seem to be stymied.

Study Objectives

This study attempts to address some of these information gaps through an in-depth case study of 149 large commercial and industrial customer accounts served by Niagara Mohawk Power Corporation (NMPC). In October 1998, with the commencement of retail access in New York, NMPC replaced the existing time-of-use (TOU) tariff for large customers with peak demand in excess of two megawatts with a day-ahead, market-based RTP rate design. This new default SC-3A service, called "Option 1", recovers fixed costs (e.g., transmission and distribution) largely through demand charges and prices electric commodity at hourly-varying prices indexed to the NYISO day-ahead market. Hourly prices for the next day are transmitted to customers by 4pm.

The NMPC customer choice restructuring plan included an additional option for commodity service, called "Option 2", whereby customers could sign up for a TOU-

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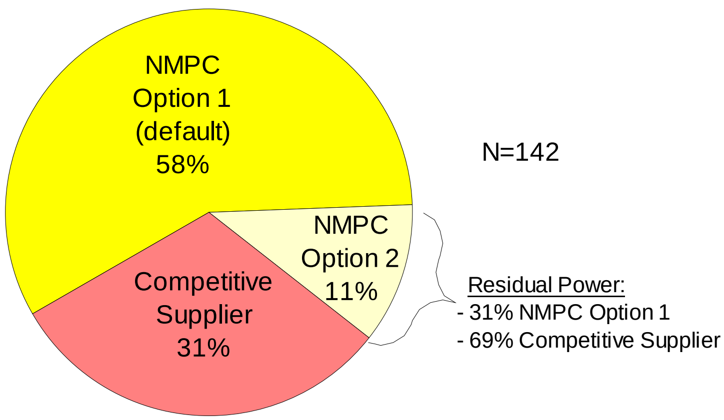
[1] A two-part RTP tariff consists of a customer baseline load (CBL) billed at the customer's otherwise applicable time-of-use tariff rate (the hedge) with only marginal usage (deviations in actual usage from the CBL) subject to hourly-varying prices.

based, fixed-rate contract offered by NMPC for up to five years on a take-or-pay basis. This alternative was offered only on a one-time basis in the fall of 1998, just prior to the opening of the retail market, and required that customers nominate monthly peak and off-peak demand blocks (at 100% load factor) for a five-year period.[2] SC-3A customers can also purchase their electric commodity service from competitive retail suppliers (referred to as ESCos in New York) providing access to indexed or hedged supply contracts and/or financial hedging products. The various supply options chosen by these customers, as of December 2002 (the most recent period for which completed data are available), are shown in **Figure ES-1**.

Figure ES-1. Supply Choices of SC-3A Customers: December 2002



Since 2001, the New York Independent System Operator (NYISO) has offered customers throughout New York state the opportunity to participate in its DR programs, which provide direct incentives to curtail load in certain hours above and beyond the SC-3A Option 1 (day-ahead) or Option 2 (TOU) prices. As a result, SC-3A customers have faced hourly prices, complemented by inducements from the NYISO that offer additional incentives to curtail load.[3]

The experience of these NMPC customers is unique and provides a rich source of information about how large customers respond to hourly electricity market prices under long-term market conditions. The overall objectives of this study are to:

- characterize customer response to and satisfaction with RTP based on day-ahead wholesale market prices in a retail competition environment;

[2] If desired, Option 2 customers could choose to nominate no load in certain periods. Option 2 customers could purchase their residual energy requirements from a retail energy service provider. Otherwise, it was priced at SC-3A Option 1 rates.

[3] NYISO offers three DR programs. The Emergency Demand Response Program (EDRP) is a voluntary program that pays a floor price of $0.50/kWh for load curtailments. The Installed Capacity/ Special Case Resource (ICAP/SCR) Program allows customers to participate in capacity markets as demand-side resources. The Day-Ahead Demand Response Program (DADRP) is an economic program in which customers bid curtailments into the NYISO Day-Ahead Market. Both ICAP/SCR and DADRP impose penalties for customers that fail to meet their curtailment obligations.

- quantify price responsiveness of various groups of customers;
- characterize drivers to customers' hedging decisions and supply choices; and
- differentiate between customer response to SC-3A prices (RTP) and to NYISO DR program incentives.

The California Energy Commission's Public Interest Energy Research (PIER) program provided funding for this study. The PIER program supports research that evaluates and assesses effective DR strategies (e.g., technologies, tariffs, programs) and facilitates the creation and distribution of DR-related information that can help California policymakers make informed decisions on the design and implementation of dynamic pricing tariffs and DR programs. Lawrence Berkeley National Laboratory (LBNL), with technical support from Neenan Associates, designed and administered the study. NMPC was an active and essential partner, providing customer load, price and account data, contributing to the study design, and supplying substantial in-kind support by encouraging customers to participate in the study. NYISO, the New York State Energy Research Authority, and the New York Public Service Commission also provided valuable assistance to the design and execution of this study.[4]

Key Findings

1. Customers are generally satisfied with RTP as the default tariff, despite the views expressed by some that hedging options are not attractively priced relative to perceived risks.

- As of summer 2003, at least 65% of survey respondents were exposed to market price volatility, either through the default RTP tariff or indexed supply contracts. However, many SC-3A customers indicate through their actions and statements that they would prefer to hedge – either through flat-rate supply contracts or financial hedges – rather than being exposed to potentially volatile SC-3A prices.
- Repeating this policy of subjecting customers to default RTP without ensuring the availability of diverse and fairly priced alternatives would likely be a harder sell today.

2. Price response is modest overall but individual customer response is extremely variable.

- Over 30% of survey respondents say they can respond by foregoing discretionary usage; 15% say they can shift (and forego) usage from peak to off-peak periods when prices get high.
- The average substitution elasticity is 0.14 for all customers.
- There is substantial variation in substitution elasticity within and between customer groups. Average elasticities by customer group are: 0.11 for industrial customers (this is comparable to other RTP studies), 0.30 for government/education customers, and 0.00 for commercial customers.

[4] The authors of this report nonetheless accept all responsibility for its contents and any errors or omissions therein.

- Extrapolating from the modeling results, aggregate demand response that could be expected from 141 SC-3A customers at a price of $0.50/kWh is ~100 MW, about 18% of these customers' maximum demand.

3. ISO-DR programs complement RTP, providing measurable increases in DR when events are called, particularly for industrial customers.

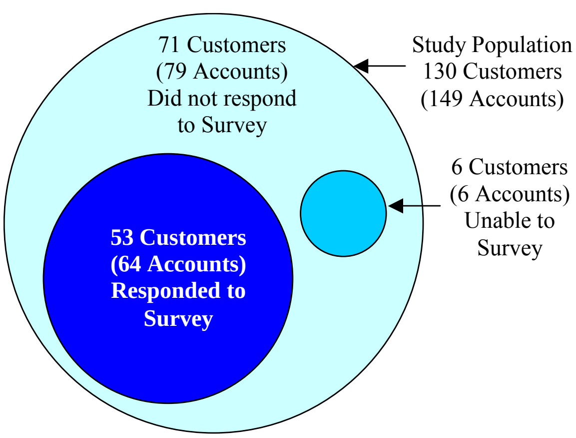
- DR-program events increase the overall amount of load curtailed by SC-3A customers by about 15%.
- Industrial DR-program participants are substantially more responsive to program events than to SC-3A prices, while for government/education customers the marginal contribution of DR programs to overall price response is modest.

4. Adoption of DR-enabling technology among SC-3A customers is modest – only 45% of customers have made investments in the five years since RTP was implemented.

Data Sources and Customer Characteristics

A self-administered customer survey and follow-up telephone interviews with a subset of survey respondents were undertaken to provide primary data. Additionally, NMPC provided basic customer characteristics, customers' hourly billing data and SC-3A commodity prices over 3-4 years.

Figure ES-2. SC-3A Population



Of the 130 customers in the study population, 124 were sent surveys in August 2003 and 53 customers, representing 64 accounts, responded (see **Figure ES-2**). Overall, the survey respondents represent the study population quite well on the basis of usage characteristics and customer supply choices (see **Table ES-1**). Almost half of SC-3A customers are government/education facilities; industrial customers represent a third of the population and the rest are commercial operations.[5] Industrial customers are slightly

[5] The government/education category includes local, state, and federal government facilities, universities, schools, and other like organizations that share an institutional decision-making structure. Commercial

over-represented in the sample and government/education customers are slightly under-represented. Survey respondents were 30-40% more likely to enroll in NYISO DR programs than the study population.

Table ES-1. Characteristics of Survey Respondents vs. Study Population

Characteristic		**Survey Respondents (N=53)**	**Study Population (N=149)**
Business Type	Industrial	40%	32%
	Commercial	21%	23%
	Government/education	40%	46%
Load Characteristics	Average Monthly Peak Demand	3.0 MW	3.4 MW
Basic Supply Choices	Option 2 Nominees	9%	18%
	Competitive Supplier*	52%	53%
DR Program Enrollment	EDRP	38%	28%
	ICAP/SCR	13%	9%
	DADRP	4%	1%

*at any time since 1998

Trends in SC-3A Prices

Two important trends in SC-3A prices during the 2000-2003 study period are noteworthy: *average* on-peak commodity prices increased significantly, while the *volatility* of on-peak prices decreased (see **Table ES-2**). These general trends hold true for all five NYISO pricing zones in which SC-3A customers are located. Zonal prices reflect differences in generation bid prices and transmission constraints.[6]

Table ES-2. SC-3A Commodity Prices (2000-2003)

Region	**2000**		**2001**		**2002**		**2003**	
	on-peak	off-peak	on-peak	off-peak	on-peak	off-peak	on-peak	off-peak
	Average Price ($/MWh)							
Capital	68.44	33.26	65.22	34.83	63.03	35.40	77.65	47.74
Central	54.98	30.39	58.89	32.50	54.84	32.24	71.93	44.07
	Annualized 30-Day Rolling Volatility							
Capital	111%	79%	43%	20%	34%	27%	17%	23%
Central	68%	54%	38%	20%	26%	20%	16%	22%

Note: *On-peak* is defined as the period from 7am – 11pm and *off-peak* is defined as the period from 11pm to 7am. All prices are for weekdays only.

facilities include retail space, office buildings, hospitals, health care facilities, and large, multi-family housing complexes.

[6] Of the NYISO zones covered by the NMPC territory, the Capital region has the highest and most volatile prices due to transmission capacity constraints. Price trends in the other four zones are similar to those shown for the Central zone in Table ES-2.

Customer Acceptance and Education

Survey respondents reported that they are relatively satisfied with the RTP tariff, despite the fact that many customers indicated that they were unprepared in 1998 to respond to dynamic prices or make decisions about procuring hedges. Only 15% of survey respondents said they would have preferred a two-part RTP tariff design, an alternative often advocated for default RTP in competitive retail markets.

How did Customers Adapt to RTP as Default Service?

The propensity of RTP customers to purchase hedges may impact their demand responsiveness and is also of interest to policymakers concerned with ensuring that adequate options exist in implementing RTP as a default service tariff. As of summer 2003, about 35% of survey respondents were hedged in some manner against commodity price risk, predominantly through physical supply contracts with flat or TOU pricing provisions. Customers report that over the past five years competitive supply offers have moved away from flat-priced hedges toward indexed deals.

About 18% of SC-3A customers selected NMPC's hedged offering (Option 2) in 1998, but these contracts expired in August 2003. On average, Option 2 customers hedged about 60% of their on-peak usage at the predetermined price schedule, with the remaining on-peak usage priced either at the day-ahead market price (Option 1) or purchased through a supply contract with a competitive retailer.

According to survey respondents, hedging product choices available during the study period were somewhat limited.[7] To characterize customers' preferences for products not necessarily available, we asked survey recipients to choose among conjoint-type choice sets of hypothetical hedge products (with a none-of-the-above option representing the default SC-3A tariff). We constructed a best possible hedge based on statistical analysis of customers' responses. This "most preferred" product would hedge 75% of customers' load during summer afternoons only, consist of a price cap of $0.06/kWh, and have a cost equivalent to 15% of the customer's annual electric bill. While this hedge was preferred over other possible hedges, it was not, however, preferred to SC-3A. Survey respondents were three times more likely to elect to face SC-3A prices than purchase this hedge. This finding suggests that in the current market context, most SC-3A customers prefer a tariff that passes through day-ahead market hourly prices to paying the implied risk premiums that were tested.

[7] Most survey respondents indicated that, particularly during the last two years, the most attractive offering from ESCos has been an index similar to the SC-3A Option 1 rate. A two mill "shopping credit" was built into the SC-3A rate; receiving this discount may have been the primary motivation to switch to an ESCO for a contract with essentially the same service and price risks.

Role of Enabling Technologies

Customers were asked if they had invested in load-management and energy-efficiency technologies at their facilities prior to and since the introduction of default RTP in 1998.[8] About 85% of survey respondents reported making largely energy-efficiency oriented technology investments prior to 1998. Since 1998, about 45% of survey respondents had made technology investments directed toward demand response (such as energy management control systems, peak-load management controls, or energy information systems). Survey respondents indicated that their price response strategies relied mainly on relatively "low-tech" curtailment solutions such as turning off lights, asking employees to reduce usage, abating HVAC operation, and shutting down discretionary equipment. Our in-depth interviews suggest that many customers are not fully aware of the potential applications and demand reduction potential of DR-enabling technologies they have adopted.

Price Responsiveness

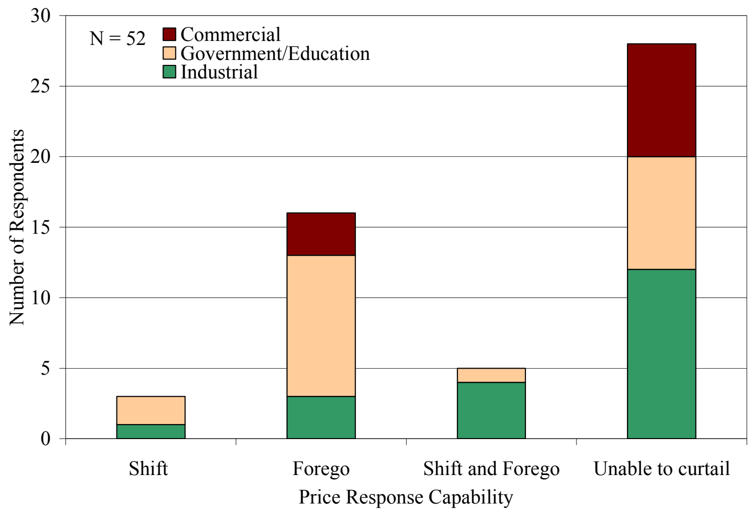
A major focus of this study was to assess the price responsiveness of SC-3A customers. We did this qualitatively through survey questions that probed customers' perceived response capability, and quantitatively through the estimation of price elasticity using demand models.

Over half (54%) of survey respondents reported that they were unable to curtail load; 31% said they could curtail by forgoing electricity usage in certain periods (without making it up at another time), 5% said they could shift load from one time period to another, and 10% said they could both shift and forego usage (see **Figure ES-3**). Overall, government/education customers were considerably more likely to indicate some type of response capability than other business types (62% vs. 40% for industrials and 30% for commercial customers).

Interestingly, almost 30% of the 28 customers that indicated that they were unable to curtail load were enrolled in NYISO DR programs, and two-thirds of them received payments for load curtailments during events. This suggests that some customers make an important distinction. To them, price response is defined by adjusting hourly usage to SC-3A prices, while curtailing load during a NYISO program event is associated with keeping the electric system secure. The former is considered a business decision undertaken explicitly to avoid high prices, while the latter imparts an intangible but important public service benefit in addition to the payment received. Thus, customers may respond to incentives to curtail on very short notice (two hours for EDRP), but may not exhibit the same response, even to a similar price incentive, when it is posted as the day-ahead SC-3A commodity rate. Our empirical price response results (below) support this distinction, at least for some industrial customers.

[8] Technologies such as EMCS, peak load management control devices, near real-time access to usage data, and energy information systems can help customers develop automated demand response strategies, reduce transaction costs to implement load curtailments, and minimize service or amenity losses.

Figure ES-3. Price Response Capability by Business Sector



Estimating Price Response

Most studies of large customer RTP employ a demand model to estimate the substitution elasticity (Herriges et al. 1993; Schwarz et al. 2002) or have modeled peak and off-peak electricity as substitutes (Patrick, 1990; Caves et al, 1984; Herriges et al, 1993; Braithwait, 2000). The substitution elasticity describes how the relative use of inputs that are substitutes in a production process changes in response to the relative prices of the two inputs. In our context, it is defined as the change in the ratio of peak/off-peak electricity consumption that results from a one percent change in off-peak/peak prices (the "inverse price ratio").[9] For large commercial and industrial electric customers, the substitution elasticity is an appropriate measure of demand response, where electricity is modeled as two substitutable commodities – peak and off-peak power – that are inputs in the production of goods or the provision of services.

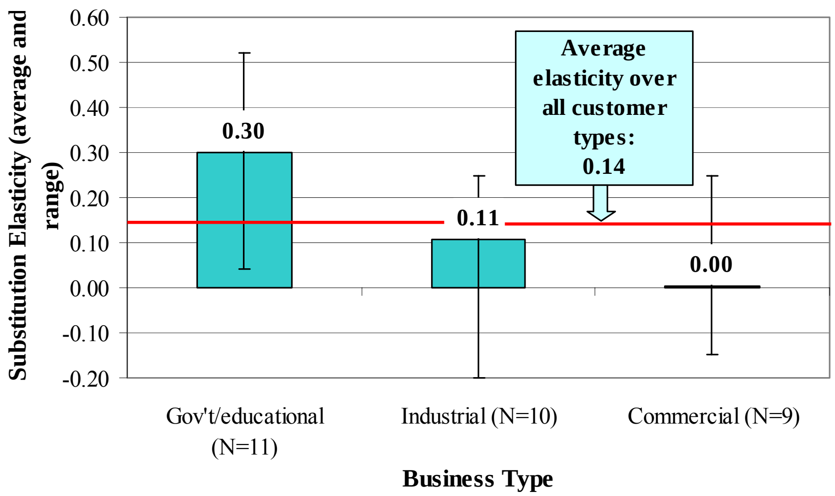
The average substitution elasticity, computed over all 32 customers for whom we had adequate survey data for modeling, is a modest 0.14. This means that a 100% change in the inverse price ratio (off-peak price/peak price) results in a 14% change in the ratio of peak/off-peak electricity consumption.[10] However, computing elasticities for each customer group reveals substantial variation, both within and between business categories (**Figure ES-4**). Average industrial customer elasticities, estimated at 0.11, are comparable to results of other RTP studies (Herriges et al, 1993; Schwarz et al, 2002). Government/educational customers are more highly elastic (0.30), which refutes the

[9] The computed substitution elasticity is a measure of how willing the customer is to shift usage given the relative prices of peak and off-peak electricity. A value close to zero indicates that even if peak electricity costs become substantially greater than off-peak electricity, the customer is unwilling or unable to shift usage. Higher, positive values indicate greater ability or willingness to shift production or service provision to off-peak hours.

[10] Assuming that typical SC-3A off-peak and peak prices are \$0.04/kWh and \$0.06/kWh, the associated off-peak to peak price ratio is 1:1.5. A 100% change in that ratio (to 1:3) would result if the peak price rose to \$0.12/kWh.

common perception that only industrial customers are good candidates for price response. Commercial customers were not price responsive (0.00).

Figure ES-4. Substitution Elasticities for 32 SC-3A Customers by Business Type



The average elasticities mask important differences in price response associated with customer circumstances. To illustrate these effects, we estimated substitution elasticities in a disaggregated fashion, first by business sector and EDRP participation, to establish a base price response, and then we estimated the marginal impact of customer circumstances and other influences on elasticities (see **Figure ES-5**).

The first table in Figure ES-5 displays base elasticities for cohorts of SC-3A customers disaggregated by business type and EDRP participation, without adjustment for any other customer-specific factors. For EDRP participants (rightmost two columns in the table) base elasticities are computed for both event days and non-event days.[11]

Under most circumstances, government/educational customers are significantly more price responsive than other customer groups; this is consistent with the average elasticity values reported in Figure ES-4. However, on EDRP event days, government/education EDRP participants are ~30% less price elastic than non-participant government/education customers. This may indicate that these customers have already curtailed or shifted load in response to SC-3A day-ahead prices when the NYISO calls an EDRP event, leaving limited opportunities to shed additional load, even at the higher EDRP inducement price. This explanation is based on the notion that some customers have a maximum amount of curtailable load.[12]

[11] During the study period, there were five days when the NYISO activated the EDRP program. On such days, during event hours, EDRP participants were assumed to face the $0.50/kWh curtailment incentive paid by the program as their SC-3A "price."

[12] Typically, EDRP events are preceded by high day-ahead market prices, which are the basis for SC-3A prices. The model we employed assumes that elasticity is constant at all prices; thus computed elasticities may be lower if prices continue to increase after customers have reached their maximum load-shedding

Figure ES-5. Impact of Characteristics and Circumstances on SC-3A Customers' Substitution Elasticities

Base Substitution Elasticity Estimates

Average Values for Customer Groups

		EDRP Participation?		
		No	Yes	
			Event Day?	
			No	Yes
Business Type	Gov't/education	0.5	0.40	0.34
	Commercial	0.26	0.18	0.06
	Industrial	0.24	0.03	0.40

Additive Impact of Other Influences

Additional Circumstances	If "yes", increment base elasticity by…
Customer factors	
Is the customer a participant in…	
...DADRP?	adding 0.33
...ICAP/SCR?	adding 0.16
Is the customer's peak usage between 12 noon and 5pm?	subtracting 0.19
Does electricity account for >10% of operating costs?	subtracting 0.08
Did the customer install DR-enabling technologies…	
...before 1998?	subtracting 0.11
...after 1998?	subtracting 0.04
Other influences	
Is the daily peak temperature higher than 70 degrees?	adding 0.02
Is the year 2001?	no effect

Industrial customers enrolled in EDRP, on the other hand, show dramatically higher price response during EDRP events compared to industrial customer response to SC-3A prices alone. For these customers, the EDRP program appears to entice price response that SC-3A prices do not.

The second set of results in Figure ES-5 shows the impact of additional factors on SC-3A customers' responsiveness that are additive to the base elasticities in the first table.[13] These results indicate that participation in other NYISO DR programs (DADRP and ICAP/SCR) enhances price response (the base elasticities are increased by 0.33 and 0.16 respectively). This is not surprising, since both programs provide financial incentives to curtail and assess penalties for non-compliance.

Customers that report peak usage between noon and 5pm and those with high electricity intensity are less responsive than other customers, all else equal. This is consistent with

capability than they would be for the same load response at lower prices. Further research using demand models that do not impose this constant-elasticity constraint, augmented by customer interviews on their curtailment potential, may help resolve this apparent paradox.

[13] For example, if a particular industrial customer were not enrolled in EDRP, its base elasticity would be 0.24. If that customer were a participant in the NYISO ICAP/SCR program, its elasticity would be augmented by 0.16 to 0.40. If that same customer experienced its peak load in the afternoons (-0.19) and had made technology investments since 1998 (-0.04), the resulting elasticity for that customer would be 0.17.

the notion that it is harder for customers to curtail when critical business activity and electric use coincide with times of high prices.[14]

However, the technology investment results are counter-intuitive. The negative marginal elasticities indicate that investing in enabling technologies actually decreases price responsiveness. This effect is much more pronounced for the energy-efficiency-type investments made before 1998. For investments made after 1998, the negative impact on elasticity is small, but we would expect these DR-oriented investments to facilitate price response. It may be that customers have received peak load management devices or information systems from NMPC or through NYSERDA programs, but have not taken full advantage of their capabilities. Another possibility is that the equipment was installed relatively recently so that it was not available during the period covered by our demand modeling.[15] Finally, investments in DR-enabling technologies may be correlated with other factors that reduce price response but are not accounted for in the model. Further research is needed to more clearly specify the impact of technology on price response.

In summary, the average estimated business class elasticities belie the diversity of response among customers within the same business classifications. Some customers are very responsive, while many do not appear to adjust their usage to prevailing SC-3A prices. Participation in the NYISO EDRP program has a positive influence on the response of some industrial customers that display little response to SC-3A prices alone. Other NYISO DR programs also appear to increase response, lending support to the notion that RTP and DR programs are complementary.

Load Response Characterization (LRC) Model

The elasticity model we used assumes that customers shift electricity-consuming activities from the peak period to the same day's off-peak period. However, many customers reported curtailing or foregoing discretionary usage during high-priced periods without making it up later (see Figure ES-3). For example, they may shut off plug loads, dim lights, and raise the thermostat setting. In such cases, the estimated elasticity of substitution underestimates the nominal level of the reduction in peak usage because it measures load shifts.

To adjust our characterization of price response to recognize these behaviors, we employed a Load Response Characterization (LRC) Model, adapting a model introduced by Patrick (1990), which distinguishes load shifting from foregoing discretionary consumption, which Patrick defines as conservation. A conservation behavior parameter is estimated from customers' hourly electricity usage data to express the degree of foregone consumption relative to a customer baseline (CBL). This parameter ranges in

[14] However, other studies of industrial response to RTP have found the opposite result: that customers with more electricity-intensive production tend to be more, not less, responsive (Christensen Associates, 2000).
[15] NYSERDA implemented programs beginning in 2001 that provided incentives to customers to install technologies that would assist them in responding to the NYISO demand response programs. However, many projects were not operational until the summer of 2002 so the cumulative impact is not reflected in the modeled data.

value from zero (complete shifting) to one (complete conservation). Values between these extremes indicate combinations of shifting and discretionary peak reductions.

Table ES-3 displays the estimated conservation parameters for SC-3A customers by business category. Average sector-specific values range from 0.85 (industrial) to 0.91 (commercial), confirming survey results indicating that customers primarily curtail discretionary usage rather than shift load. The estimate ranges in Table ES-3 bound the results within each business classification.[16]

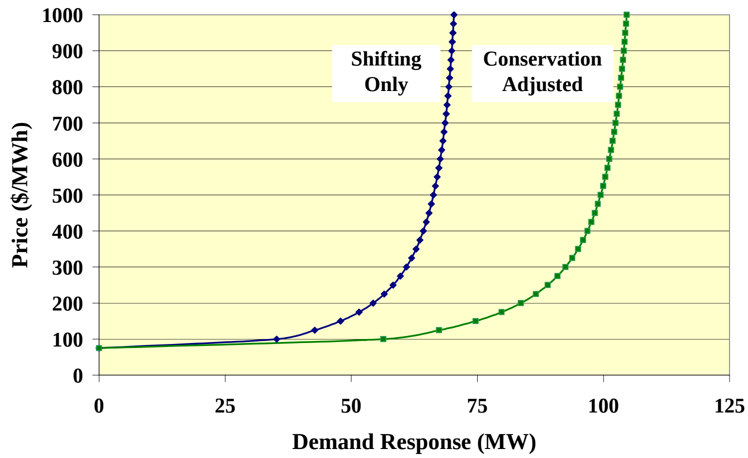
Table ES-3. Conservation Parameter Estimates

Business Type	Number of Customers	Average Conservation Coefficient	Estimate Range
Industrial	10	0.82	0.50 – 0.92
Commercial	9	0.91	0.64 – 1.00
Gov't/education	11	0.85	0.64 – 1.09

Aggregate Demand Response Potential of SC-3A Customers

We used substitution elasticity and conservation parameter estimates to predict the level of demand response that can be expected from high-price events. This provides a comprehensive estimate of the aggregate response of SC-3A customers that accounts for both types of curtailment behavior.

Figure ES-6. Aggregate SC-3A Peak Period Demand Response: Shifting Only and Conservation Adjusted



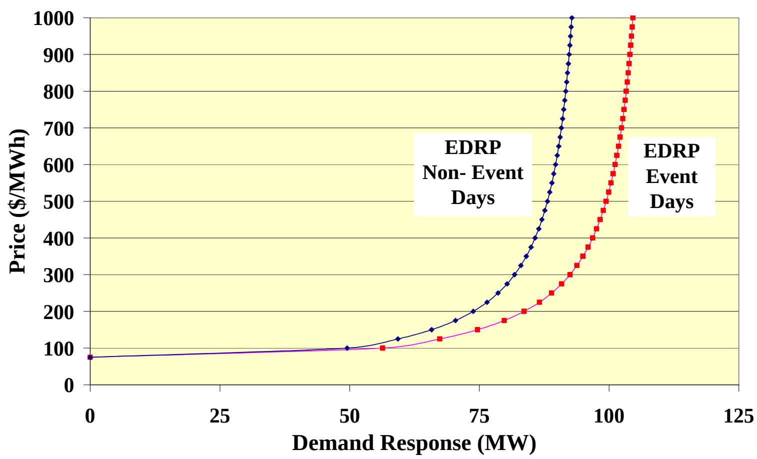
To estimate the peak-period price response of SC-3A customers as a group, the elasticities for the four business sectors were extrapolated to the population of SC-3A

[16] Parameter estimates greater than 1.0 indicate that the customer reduces load by a greater proportion in the off-peak period than is curtailed (foregone) in the peak period.

customer accounts, using sector load weights.[17] **Figure ES-6** illustrates the resulting peak period curtailment curves, first using the estimated substitution elasticities alone (shifting behavior), and then incorporating the estimated conservation effect. At a reference price of $0.50/kWh, almost 30 MW of additional demand response is attributable to curtailing or foregoing discretionary usage. Over 90% of the curtailment potential is achieved at a price of $0.50/kWh. The maximum curtailment amounts to about 18% of the non-coincident peak demand of the SC-3A customer class.[18]

Figure ES-7 illustrates the interrelationship between the SC-3A tariff rate and EDRP in providing demand response. The declaration of an EDRP event by the NYISO provides about 12-15 MW of the estimated curtailments by SC-3A customers.

Figure ES-7. Estimated Impact of EDRP Events on SC-3A Customers' Peak Period Demand Response



Implications for Policymakers in California and Other States Considering RTP Adoption

The findings of this study provide important insights for policymakers interested in facilitating the development of price-responsive load through RTP and/or DR programs.

Which will better achieve socially optimal levels of demand response – imposing default RTP or implementing emergency DR programs?

The NMPC experience shows that large customers are likely to provide a moderate amount of demand response when RTP is their default service tariff, even if some customers hedge against price volatility. However, subjecting customers to wholesale market variability is not sufficient to realize their full demand response potential. DR

[17] The elasticities were estimated using 32 customers with complete survey data; elasticity results were matched and extrapolated to the 141 SC-3A accounts with a maximum peak demand of 562 MW.
[18] Customers' peak demand was established individually from their usage during the weekday hours of 7am – 5pm.

programs that target payments to specific market conditions that arise after day-ahead prices have been posted provide supplemental load curtailments that produce significant benefits. The debate should not be focused on the choice between these designs, but on how to use both to best advantage.

Are industrial customers the most likely source of price response?

The NMPC results challenge conventional wisdom, indicating that the ability and inclination of customers to respond varies widely:

- Government/educational customers are most responsive to SC-3A prices, not industrial customers. Since these entities are common in virtually every jurisdiction, the potential for RTP is perhaps greater than previously envisioned.
- Estimated industrial customer elasticities are comparable to studies of two-part RTP programs, but NYISO DR program participation doubles their responsiveness.
- A key challenge is in enhancing the price responsiveness of commercial sector customers. Because certain commercial customers (e.g., office buildings) have similar physical characteristics and end use loads (e.g., space conditioning and lighting) to government/education facilities, response from this sector is at least technically feasible. If institutional and other barriers can be overcome, the commercial sector may provide a rich source of price response.

What are appropriate transition strategies to default RTP?

The NMPC experience indicates that there is a gap between what customers consider to be a fair hedge cost and what the market offers. Future market-based RTP initiatives should consider providing utility-supplied hedging options initially, especially if smaller, less experienced customers are involved, so that customers can choose the level of risk exposure they are comfortable with. Such offerings should entail shorter contract terms than NMPC's Option 2, provide more flexibility, and be implemented only for a well-specified transition period.

Are enabling technologies a necessary condition for price response?

No – a wide range of NMPC customers demonstrated that they can and will adjust loads manually if the incentive is sufficient (e.g., high prices, perceived emergency conditions). However, over the long term, without automated response, the amount of load shifted or foregone is likely to be limited and is probably not sustainable. The NMPC experience demonstrates that many customers are not aware of available price response technologies and strategies. Targeted customer education and assistance to invest in DR-enabling technologies and develop response strategies are necessary to realize customers' inherent price response potential.

1. Introduction

The experience of the past few years has demonstrated the propensity for extreme price volatility in restructured electricity markets. Thus, there is increasing interest in policies, programs and tariffs that encourage customer loads to provide demand response (DR) to help discipline wholesale electricity markets. Conceptual studies and market simulations suggest that if a sufficient number of consumers are exposed to and adjust their demand in response to wholesale electricity market prices, the resulting load reductions will limit the ability of suppliers to increase spot and long-term market-clearing prices above competitive levels (Borenstein, 2002; Ruff, 2002). In California, in the aftermath of the 2000-2001 electricity crisis, state policymakers have made a strong commitment to promoting demand-side resources as part of a strategy to prevent extreme price spikes and mitigate market power.

While in theory these benefits are enticing, in practice there is substantial debate about how to create sufficient price-responsive load to enhance the efficiency and competitiveness of wholesale electricity markets. There is not even consensus on what constitutes enough demand response. Historically, a significant number of commercial, industrial and residential customers have been exposed to time-of-use (TOU) rates.[19] However, TOU rates, because they are preset for pre-determined hours and days months to years in advance, mask the actual hourly variability of wholesale market prices and are consequently not very effective at easing tight wholesale market supply conditions (Borenstein, 2002). Historically, many utilities have offered interruptible rates to their large industrial customers that typically provided a discount or bill credit toward their applicable tariff rate in return for the agreement to reduce load on short notice, or face a significant financial penalty. However, interruptible tariffs provide limited insight into how customers respond in terms of price elasticity, because of how they were utilized (as a last recourse), their design features, and because few programs have been evaluated.[20]

Dynamic pricing tariffs allow retail prices to be adjusted frequently and on short notice to reflect changes in wholesale market prices (prices may vary over different hours of the day and for different days). A number of analysts have argued that real-time pricing (RTP) represents the most direct and efficient approach to inducing demand response and that, therefore, this should be the emphasis of policymakers' efforts (e.g., Borenstein, 2002). About 40 utilities have experimented with RTP tariffs over the last two decades (Barbose et al, 2004). A few programs have persisted over multiple years, managed to achieve and/or maintain substantial customer participation, and have reported elasticity estimates and aggregate demand response under various pricing conditions, most notably Niagara Mohawk (Herriges et al, 1993), Georgia Power (O'Sheasy, 2002) and Duke Energy (Schwarz et al, 2002). However, most other utilities with RTP tariffs currently

[19] Conventional wisdom is that a well-designed TOU rate can induce customers over the long-term to alter the pattern of their daily and/or seasonal demands through a combination of behavioral changes and equipment investments, although few TOU programs have been subject to formal evaluations and econometric analysis (see Christensen Associates, 2000; Neenan Associates, 2003).

[20] The terms of most interruptible tariffs make it difficult to observe actual price changes in relation to changes in usage. This makes it difficult to estimate price elasticities applicable to other tariffs.

have no more than a handful of customers enrolled.[21] Overall, less than one percent of electricity customers in the U.S. have faced retail rates that pass through hourly prices observed in wholesale markets.

It is also worth noting that the market context for nearly all of these RTP programs is quite different than the situation California and many other states today face. For example, nearly all have been voluntary programs implemented by vertically integrated, regulated utilities that operate in states without retail competition. By contrast, in many states that are now considering RTP, retail electricity markets have been opened to non-utility service providers and RTP adoption is often framed in terms of the appropriate tariff design and structure for default utility service for customers. Moreover, nearly all RTP experience thus far has utilized a two-part, revenue-neutral tariff design, in which a customer's typical usage level and load shape pattern define a customer baseline load (CBL), which is priced at the regulated tariff rate, and any incremental usage above or below the CBL is charged the hourly-varying price. Thus, this RTP structure amounts to a hedge; the customer's overall financial exposure to price variability is typically much lower than for a one-part RTP tariff in which the customer is billed for all usage at hourly-varying prices.

Finally, other analysts have suggested that implementing ISO- and utility-sponsored demand response programs that offer customers occasional opportunities to be paid market prices for load curtailments could have a large and possibly more immediate impact on reducing wholesale price volatility (Neenan et al, 2003). In this approach, customers (alone or working with load serving entities) either bid curtailments directly into day-ahead markets or agree to curtail when asked by an ISO or utility during emergencies and receive compensation based on a prevailing market price.

On what basis should policymakers select from among the various rate and program alternatives to achieve the objective of increased demand response? Which of these approaches makes the most sense for various customer groups? All approaches rely upon assumptions regarding customers' price elasticity, the level of price response by different customer groups, factors that affect customers' ability to respond, identification of barriers to RTP, and customer preferences for physical and financial hedging products. Yet, to date, relatively little information exists in the public domain about how customers actually respond to RTP in the context of current prices and emerging competitive market and institutional structures.

This study attempts to fill some of these information gaps through an in-depth case study of approximately 130 large industrial, commercial and institutional customers served by Niagara Mohawk Power Corporation (NMPC). With the introduction of retail customer choice in November 1998, NMPC's largest (over 2 MW) customers were given the

[21] Participation levels are modest for several reasons: (1) the base of eligible customers is small (e.g., pilot programs with capped participation or programs limited to very large customers), (2) limited marketing efforts by the utility, (3) significant customer attrition at some utilities, driven primarily by rises in marginal electricity prices and/or price volatility, and (4) limited savings opportunities because of small price differentials.

choice of a default service tariff in which their hourly prices for electric commodity are derived from the NYISO's day-ahead market (DAM) prices or a tariff with fixed commodity prices for up to a five-year period.[22] Under the former, customers are exposed to day-ahead wholesale market volatility. The latter provided a hedge against that price volatility. Alternatively, customers also had the option of procuring commodity service from a competitive retail supplier (referred to as an ESCo in New York) and/or of purchasing various types of financial hedging products.

This study was funded by the California Energy Commission's Public Interest Energy Research (PIER) program. The CEC PIER program is supporting research that evaluates and assesses effective demand response (DR) strategies (e.g., technologies, tariffs, programs) and facilitates the creation, location, and distribution of DR-related information that can help California policymakers make informed decisions on the design and implementation of dynamic pricing tariffs and DR programs. The overall objectives of this study are to:

- characterize customer response to and satisfaction with RTP based on day-ahead wholesale market prices in a retail competition environment;
- quantify price responsiveness of various groups of customers;
- characterize drivers to customers' hedging decisions and supply choices; and
- differentiate between customer response to SC-3A prices (RTP) and to NYISO DR program incentives.

The experience of NMPC customers is unique and provides a rich source of information about how customers respond to day-ahead electricity market prices over a relatively long time period. As part of the study, Lawrence Berkeley National Laboratory (LBNL) with Neenan Associates[23] developed and administered a written survey, conducted telephone interviews with a sub-set of survey respondents, and analyzed ~3.5 years of hourly billing data for individual customers to develop estimates of customer price responsiveness. Distinctive features of this study include:

- significant representation from commercial and institutional sector customers as well as large industrial firms,
- a rich multi-year dataset of hourly prices and customer consumption data during which customers saw occasional high prices due to extremely hot weather and system emergencies,
- survey information on customer characteristics, rate and contract history, organizational decision-making, customer satisfaction, awareness and preparedness, and adaptation and coping strategies that addresses key policy questions that arise in implementing large RTP programs, and

[22] NMPC's RTP offering is most accurately characterized as a one-part RTP tariff based on hourly day-ahead market prices. Under this tariff, NMPC incurs balancing risk that is effectively born by non-RTP customers through a commodity adjustment charge (CAC).
[23] Neenan Associates was a subcontractor to LBNL on this project.

- efforts to understand customer choices with respect to supply and hedging options and participation and performance in ISO demand response programs.

While this report is tailored to RTP-related policy questions currently being explored in California, its implications are relevant for any state or agency considering RTP implementation in a competitive market context or for demand response goals.

This report is organized as follows. Our approach, data sources, methods used to analyze customer preference and choices and to model customer electricity demand are outlined in Chapter 2. In Chapter 3, we describe the historical evolution and market context for adoption of RTP as the default service tariff at NMPC, summarize key features of the RTP tariff design, and describe other supply and service options available to large industrial and commercial customers in the NMPC service territory. Results from the customer survey and in-depth interviews are presented in Chapter 4, and customers' revealed preferences and choices with respect to choice of supplier, extent of hedging to mitigate price volatility, and decisions to participate in NYISO DR programs are explored. In Chapter 5, we summarize survey research on customers' stated preferences for hedging products. Chapter 6 reports customer demand modeling results, including elasticity estimates, load response characterization and aggregate demand response estimates. In Chapter 7, we summarize key findings and discuss implications for policymakers and program designers in California and other states in the following areas: RTP tariff design and retail market structure, implementation issues and customer acceptance, customer coping and response strategies, role of enabling technologies, interactions between RTP and DR programs, and demand response potential of RTP.

2. Approach

The NMPC SC-3A tariff represents the first large-scale application of real-time pricing (RTP) in a competitive retail market in the U.S. The program has attracted the interest of policymakers in both California and elsewhere interested in assessing alternate approaches to pricing default service as it provides a unique opportunity to measure customer acceptance of RTP tariffs, characterize and evaluate customer strategies to adapt to RTP, and quantify customers' response to market prices over an extended period. In this chapter, we describe the methodologies used in this study, including: collection and analysis of customer billing and survey data, interviews with regulatory staff and other key stakeholders, customer market research, and models of customer preferences and price response.

2.1 The Role of Niagara Mohawk Power Company

NMPC provided substantial in-kind support that was essential to the execution of this study, providing customer account, contact information, billing and usage data for SC-3A customers from its Customer Service System (CSS), and encouraging customers to participate in the study and respond to the survey. The customer billing and usage data provided by NMPC included a comprehensive set of SC-3A customers' hourly interval meter and price data from spring of 2000 through early summer of 2003. Additionally, NMPC provided summary information on all large customers in its service territory, including those not served under the SC-3A class (e.g., number, peak demand and SIC code of customers on each tariff). NMPC and LBNL negotiated and signed a Non-Disclosure Agreement (NDA) that deals with treatment and disclosure of confidential customer information as well as a Memorandum of Understanding (MOU) that describes the goals, objectives, roles and responsibilities of each party.

2.2 Access to NMPC Customer Billing and Survey Data

Based on the provisions of the NDA, LBNL agreed not to disclose confidential information on any individual customers (such as name, contact information, account number or information) or portray results that might compromise an individual customer's identity or circumstances. In conducting customer surveys and in-depth interviews, customers were given assurances that their answers and comments would be confidential. The NDA allows LBNL to report and publish results in a manner that protects the identity of the individual customers and still effectively convey their experiences.

2.3 Interviews with Regulators and Industrial Customer Representatives

To understand the context for the adoption of real-time pricing as the default service tariff for NMPC's largest customers, we conducted interviews with staff of the New York Public Service Commission (NYPSC) and industrial customer representatives. The interviews were conducted in November 2002 and included questions on the regulatory process and key policy issues pertaining to the RTP tariff, major tariff design issues, the relative importance of various criteria and policy objectives, implementation costs, and the relationship between RTP and NYISO DR programs. The protocol used to guide regulator interviews is included in **Appendix A.** Much of the discussion in Chapter 3 is drawn from these interviews.

2.4 Analysis Framework

To guide survey development and subsequent analyses, we developed the framework shown in **Figure 2-1**, in which we identified a number of customer-specific factors that we hypothesized were potential drivers for customer choices and performance under the SC-3A pricing regime. We examined the following choices that customers faced: (1) whether to nominate load under the flat rate alternative to RTP offered by Niagara Mohawk, (2) whether to switch to a competitive electric commodity supplier, and if so, what type of product to choose (e.g., hedged vs. indexed), (3) whether to purchase financial hedging products, and (4) whether to participate in NYISO DR programs. Performance, in this context, refers to the change in consumption in response to varying hourly prices. Drawing from this conceptual framework, we developed a series of formal hypotheses that were tested using several analysis methods (see **Appendix C**).

Figure 2-1. Factors Affecting Choice and DR Performance

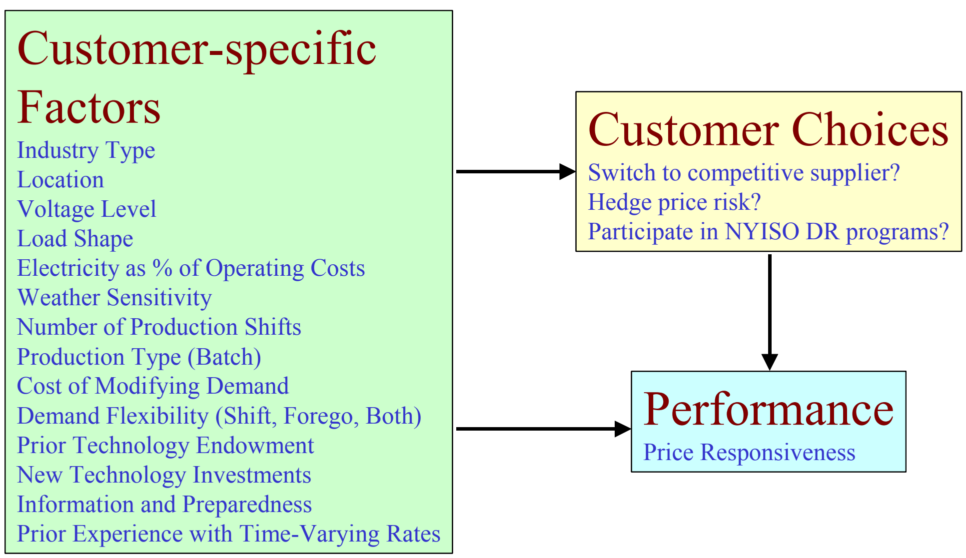


Figure 2-2 provides an overview of how we analyzed the interaction of customer-specific factors, choices and performance. Customer choices were examined in a "top-end" analysis in which we examined relationships between customer characteristics, circumstances and perspectives and the choices they made using simple statistical tests (ANOVA). We also utilized more structured behavioral models that characterize revealed and stated preferences (see section 2.6). Customer performance (price responsiveness) was assessed through estimation of demand models and characterized by deriving price elasticities (see section 2.7).

Figure 2-2. Analysis of Customer Choice and Response

	Analysis Method	Explanatory Variables
Customer Choices		
Option 2	Top-End	Customer Factors
Competitive Supply	Top-End, Revealed Preference	Customer Factors
Hedging	Top-End, Revealed Preference, Stated Preference	Customer Factors & Choices
ISO DR Program Participation	Top-End	Customer Factors & Choices
Customer Response		
Price Response	Demand Models	Customer Factors & Choices

Christensen Associates (2000) identify three drivers for price responsive behavior: (1) *incentives* (e.g., relative peak and off-peak prices), (2) *ability to shift load* (e.g., installation of enabling technologies), and (3) *willingness* to do so (e.g., organization and business practices). Most of the customer factors in Figure 2-1 may be viewed in terms of these three categories. However, we add two additional drivers to this list. First, we separate informational factors affecting load-shifting ability from physical ones, and we group these with customer experience/exposure to time-varying rates in a fourth driver: *prior experience/knowledge*.[24] Second, we include *customer alternatives* as an explicit, fifth driver that corresponds to the choices in Figure 2-1. Customer response to time-varying electric rates should not be viewed in isolation from the overall structure of the electricity market. Depending on market structure and design, customers will have a variety of alternatives to choose from that may impact their response to RTP. This is especially true in the context of retail competition where customers have more choices. For example, the availability and attractiveness of hedged supply contracts offered by competitive suppliers and DR programs offered by ISOs and tied directly to wholesale markets may play an important role in determining customer response to RTP.

We explored these five drivers with customer survey questions and customer characteristics and billing data from NMPC, as outlined in **Table 2-1**.

[24] While it would be tempting to attribute information and experience to *willingness*, (for example, we may hypothesize that a customer with prior experience on time-varying electric rates will be more willing to respond) the one does not necessarily follow the other.

Table 2-1. Drivers for Price Responsive Behavior and Associated Customer Factors

Response Driver	Customer Factors
Incentives	Electricity expenditures relative to total operating expenses
	Cost of modifying demand to support different levels of DR action
	Minimum price required by customer to initiate curtailment
	Customer location (regional differences in the level and volatility of prices)
Ability to shift load	Load Shape (daily, weekly and annual)
	Weather sensitivity of loads
	Production or firm activity attributes – batch processes, number of shifts per day
	Demand flexibility – specification and size of loads, onsite generation capacity
	Type of response capability – shifting, foregoing or both
	Types of actions taken in response to high prices
	Recovery time after DR actions
	Investments in load-management and energy-efficiency technologies
Willingness	Energy procurement decision-making
	Satisfaction with RTP programs
Prior Experience/ Knowledge	Prior experience with time-varying rate structures
	Exposure to information on energy procurement, hedging, enabling technologies and response strategies
Customer Alternatives	Decision to nominate load on Option 2 (the NMPC fixed rate alternative to RTP)
	History of purchasing electric commodity from a competitive supplier
	Types of competitive supply arrangements taken (flat rate vs. indexed)
	Types of financial hedging products purchased
	NYISO DR program participation
	Preferences for hypothetical hedging products (conjoint survey)

2.5 Customer Market Research

A distinguishing feature of this study is our attempt to augment customers' billing data with comprehensive market research of the target customer population. This market research provides conditioning variables that improve the performance of customer demand models, as well as providing insights into customer awareness, acceptance, and willingness to respond and/or adapt to hourly prices through various coping strategies.

Our market research consists of two elements: (1) a self-administered written survey and (2) in-depth telephone interviews with a subset of customers that answered the written survey and agreed to a follow-up interview. Both the survey and interviews were administered between August 4 and September 18, 2003.[25] To encourage participation, customers that filled out the written survey were entered into a drawing for several prizes.[26]

[25] The survey period was extended due to low response rates following a major internet worm in early August and the Northeast blackout of August 14-15.

[26] LBNL sponsored the survey and prizes. Four winners were selected in the drawing among the 53 customers that responded and filled out the written survey. Winners could choose between two prizes (a home theatre system or a digital camera) each valued at around $450. Customers that volunteered for a follow-up telephone interview were also entered into a second prize pool for a weekend trip for two to Niagara Falls (of comparable value to the other prizes).

2.5.1 Customer Survey

The written survey consisted of 55 direct survey questions as well as a conjoint survey of 19 hedging choice sets (the full survey is included in **Appendix B**). The survey instrument was primarily administered as an Internet-based form, but customers could also complete a hard-copy survey and return it by fax or post. Over 75% of respondents used the web-based version.

The first portion of the survey included questions about firm characteristics and equipment, experience with dynamic pricing tariffs prior to 1998, satisfaction with the SC-3A tariff, customer access to various types of information, investments in enabling technologies, price response strategies, choices made for competitive supply options and financial hedging products, and experience with NYISO DR programs. The conjoint section of the survey presented customers with 19 choice sets that asked them to trade off among attributes of a series of hypothetical hedging products.[27]

In-depth Interviews as Complement to Customer Demand and Choice Models

As part of this study, we also conducted in-depth interviews with 29 survey respondents, which served multiple functions: (1) supplied additional supporting information that enabled us to better interpret survey responses, (2) provided a quality control mechanism for the written survey which helped us assess how well customers understood the survey questions, and (3) provided a framework to explore customers' responses and choices with respect to RTP, framed in their own terms. The assumptions regarding customers' decision-making framework (and trade-offs) that are the drivers in demand models are not always easy to combine or reconcile with the ethnological approach, as embodied in in-depth interviews.[1]

Our in-depth interviews focused primarily on understanding *why* particular customers responded, performed and chose as indicated. We tried to elicit a set of customer-centered stories. The strength of such story-centered descriptions is their ability to highlight path dependencies and causal or at least functional relationships. However, there are several challenges in implementing this approach. First, interesting stories are often closely linked to particular characteristics of a customer (e.g., load response capability may be influenced by the specific industrial processes, load shapes, or labor inputs). Because of the need to protect customer confidentiality, however, such details cannot be revealed. Under these conditions, many stories lose the essential drivers to their plots. In sum, almost every customer has a special situation; we just can't say what it is. Even so, stories are included in generic form. Second, in interpreting customer responses, it is important to recognize that customers may provide answers that are "strategic" in the sense that they support their perceived interests or concerns in the regulatory process. For example customers may say that they can't shift load if they believe that regulators may institute a tariff that mandates them to do so. However, these strategic comments are an essential part of understanding customer response as well.

[1] See Asad (1994) for a discussion of the challenges and potential benefits of combining quantitative and ethnographic approaches for policy questions.

[27] See section 2.6.2 for a more detailed discussion of the conjoint survey.

2.5.2 Follow-up, In-Depth Interviews

LBNL staff interviewed customers that volunteered for follow-up telephone interviews. The in-depth interviews were typically about 20-25 minutes in length (though some extended up to 60 minutes) and gathered additional information on several specific topics: (1) understanding factors underlying customers' choice of supplier and tariff options (2) chronology of market interactions and customer experience with retail suppliers, (3) customer attitudes, views and perceived price response capability, (4) coping strategies and barriers, and (5) organizational decision-making structure and process.[28] These questions were synthesized into a semi-structured interview protocol customized for each customer based on initial survey responses, but customers were encouraged to discuss other issues of importance to them as well. We highlight results of in-depth interviews in text boxes.

2.5.3 Customer Response

Customer response to the survey is summarized in **Table 2-2**. Fifty-three customers (representing 64 different premises) responded, out of a population of 130 customers.[29] Most (68%) of the written survey respondents volunteered for follow-up telephone interviews. We ultimately conducted follow-up interviews with 29 respondents; some customers could not be reached or scheduled within our survey window.

Table 2-2. Response to Customer Survey

Survey Phase	Number of Respondents
Base Survey	53
Conjoint Survey	45
Volunteers for follow-up interviews	36
Completed follow-up interviews	29

2.6 Modeling Customer Preferences and Choices

In recent years, the focus of econometric analysis has shifted from aggregate models that describe markets as a whole to disaggregate models of the individual decision-making units that underlie market demand and supply (Train, 1985). Two approaches are typically employed to analyze customers' decision-making processes. The revealed preference approach focuses on the observed choices actually made by consumers – in this case electricity-purchasing decision-makers. Stated preference analysis involves characterizing customer preferences for hypothetical or representative choice sets. Both of these models were used to characterize customers' decision processes using survey responses and other customer information garnered from billing records.

[28] We selected topics that were high priority areas of the study and also where "open-ended" questions and interactions with an interviewer allowed us to focus on various "why" questions – e.g., Why did you choose a competitive supplier? Why do you say that you can't curtail?
[29] See section 4.1.1 for a detailed discussion of the population of SC-3A customers and their associated accounts.

2.6.1 Revealed Preferences

We developed and estimated a choice model using survey responses and other customer data in order to identify the key drivers to, and their relative influence on, customer's observed decisions regarding (1) their choice of supplier (see section 4.3.2.1) and (2) whether to fully hedge against price and volatility risk (see section 4.3.5.1).

Following economic theory, we posit that these choices are driven by customers' calculations of the marginal benefit of each choice.[30] Customers are assumed to act rationally, choosing options that provide the greatest benefit. For example, if the net benefit of choosing a competitive supplier over staying with the utility is positive, then we assume that the consumer would choose to switch to a competitive supplier. Thus, modeling choice involves ascertaining the expected benefit (or utility) of the consequences of that choice. However, the marginal benefit of choices cannot be observed or quantified easily.

As described by Neenan (2002), the net benefit, or the difference between the marginal cost and marginal benefit of a choice, can be represented statistically as:

(1) $Y^* = \beta' X + \varepsilon$

where Y^* is the expected net benefit of the choice, the vector X contains the factors that determine the net benefit of the decision, β' is a vector of parameters that quantifies the influence of each element of X on Y^*, and ε is the error term that has a logistic distribution with zero mean and unit variance.

Since we can only observe the actual decision Y, we assume that if $Y^* > 0$ then $Y = 1$ and if $Y^* < 0$ then $Y = 0$. This describes the decision in a discrete representation based on observed behavior. For example, the customer either signed a hedged contract or tariff, or did not.

Since Y can take only two values, 0 and 1, two of the five underlying assumptions of the standard regression model are violated. Hence, we use the Logit formulation described in Neenan et al (2003) to model the probability of $Y = 1$. In the Logit formulation, the probability, a number bounded by 0 and 1, is converted to an odds ratio that is non-negative and not bounded, and therefore takes on continuous, positive and negative values. Using this logarithmic transformation of the odds ratio, we can model customers' choices with the standard regression model, using the maximum likelihood technique described in detail by Allison (1999).[31]

2.6.2 Stated Preferences

The focus of revealed preference modeling is limited to decisions made by customers from the alternatives available to them. The customer survey and follow-up interviews

[30] See Train (1985) for a complete description of the economic foundation for modeling customer choices.
[31] The regression was performed using the "PROC LOGISTIC" procedure in SAS.

indicate that a limited set of hedging options were available to SC-3A customers during the study period. However, policy makers are interested in customer's preferences for a wide range of possible hedging products. To extend our understanding of customers' hedging preferences, we conducted a stated preference analysis, administering a structured (conjoint) survey instrument to induce customers to reveal their preferences for product features, and then applying choice theory to estimate the contribution of product features to customer preferences.

Conjoint surveys make use of a branch of marketing and economic research known as discrete choice analysis, and have the goal of understanding the motivations behind choices for hypothetical products or services (Allison, 1999). The conjoint survey administered to SC-3A customers (shown in **Appendix B**) contained 19 different choice sets.[32] Respondents were asked to choose from four different hedge products or a "none of the above" option representing the default SC-3A RTP rate.

The products in a choice set are purposefully varied combinations of a fixed set of basic product features. In this case, the features tested are the basic building blocks of electricity hedges: (1) the amount of load hedged (as % of total customer load), (2) the commodity price and hedge premium (price level in $/kWh and hedging premium expressed as a percentage of the monthly electricity bill), (3) the pricing method used in the hedge contract (capped or average price), (4) hours of the day covered by the hedge (noon to 10pm, 6am to noon, noon to 6pm), and (5) the months of the year covered by the hedge (summer only, winter only, summer and winter, all year). The limited number of feature values represents a compromise between granularity and the corresponding number of choice sets required in the conjoint survey.

Each question, or choice set, presents the survey respondent with several alternative products, configured from a common set of features but differing in the level of those features. From each set, the respondent selects the product he or she most prefers.[33] The respondent's choice in each set constitutes an observation on his or her stated preferences for the specific product and features tested by the set, and the full set of choices collectively provide the basis for estimating preferences for individual product features. We compiled the answers to the 19 questions and calculated utility levels for each of the different feature levels. See **Appendix D** for a detailed discussion of our methodology.

As described by Neenan (2002) the utility for each choice can be represented mathematically as U_j as follows:

(2) $U_j = \beta' Z_j + \varepsilon_j$

where Z_j is vector of feature levels, β' is a vector of the parameters to be estimated and ε_j is an error term that has a conditional logit distribution. If the customer chooses product j

[32] All respondents faced the same set of choices.

[33] The number of choice sets is determined by what is needed to ensure that the range of product features being explored is sufficient to achieve a valid statistical representation of the entire universe of products containing all permutations of product feature levels.

in a given choice set, then that product is assumed to provide the most utility among all the j alternatives.

The Logit formulation is transformed from a number bounded by 0 and 1 into a log odds ratio that is unbounded, making it more suitable for statistical estimation. The survey responses are tied together over the entire 19 choice sets seen by each respondent. This results in a slightly different method for estimating utility levels than in the revealed preference analysis discussed above.[34]

2.7 Modeling Customer Electricity Demand

2.7.1 Conceptual Overview

Understanding and characterizing customer price response is critical to creating more robust competitive electricity markets and integrating DR into resource portfolios. In order to accurately estimate the value of DR, it is important to identify how many and which types of customers are responsive and to quantify that response relative to prices and other driving influences.[35] But it is equally important to identify customers that are *not* responsive, as they are most impacted by price volatility and most concerned with the availability of applicable and reasonably priced hedging products.

SC-3A customers are large commercial or industrial enterprises engaged in industrial activities (e.g., extraction, manufacturing, fabrication, assembly, transportation and distribution), public services (water, sewer and power), educational or government services, or commercial services (e.g., wholesale hubs, retail stores and restaurants). These firms are engaged in economic activity to which electricity is an input. Consequently, we model electricity use as the derived demand of an input into their productive and business processes as these firms seek to minimize the overall cost of these processes. Given their exposure to hourly prices that exhibit distinct temporal and diurnal price variations, we postulate that SC-3A customers consider electricity as two distinct commodity inputs, peak and off-peak usage, that may be substituted for one another. The appropriate measure of price response is the substitution elasticity, which measures how inputs can be substituted for one another to meet a firm's output obligations.

Figure 2-3 illustrates the data and analytical models used to characterize the price response of SC-3A customers. In the following sections, we describe the data collected, the variables constructed to support this analysis, and the models estimated.

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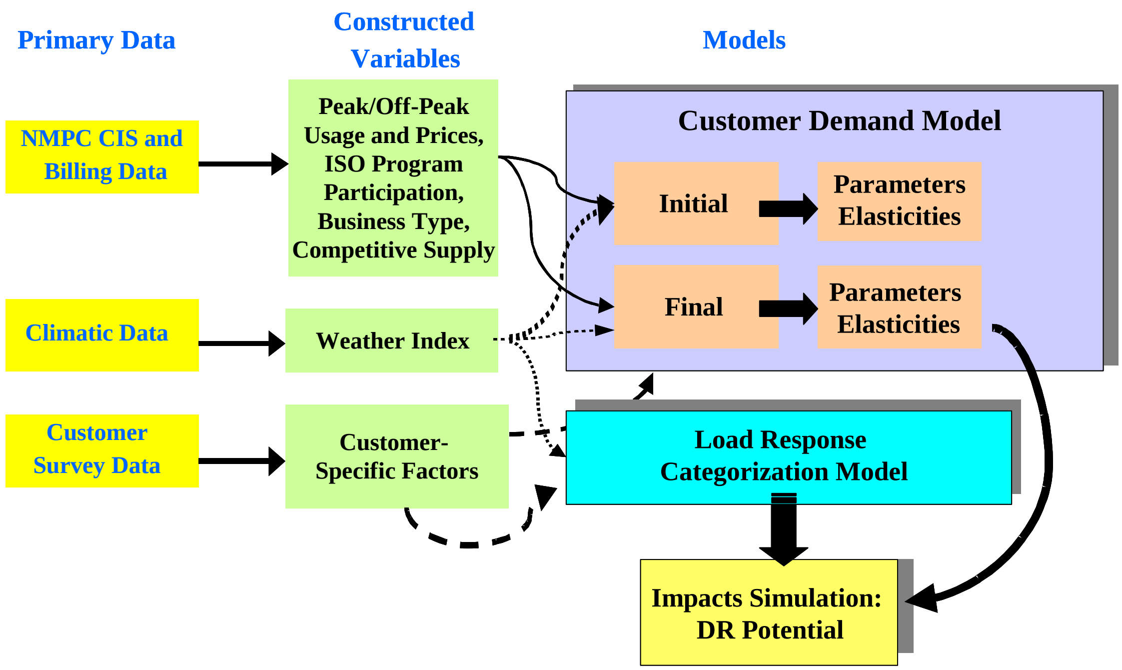
[34] Although the maximum likelihood technique is still retained, the SAS procedure PROC PHREG is uniquely capable of handling discrete choice models and as such was used to estimate the model herein (Allison, 1999).

[35] The benefits of price response go beyond the bill savings that customers realize, and include lowered price risk for all consumers. See Neenan et al (2003) for a detailed discussion of the benefits of price response.

2.7.2 Primary Data

NMPC provided hourly usage data for 141 SC-3A customer accounts from the spring of 2000 through mid 2003. We used billing records and other information to determine if customers had elected the SC-3A Option 1 or 2 rates, switched to a competitive supplier, or had participated in a NYISO demand response program. Historical SC-3A prices by region and voltage zone were downloaded from NMPC's website. Climatic data for representative locations throughout the NMPC service territory was collected for use in constructing a weather index.

Figure 2-3. Modeling Electricity Demand and Simulating Price Response



2.7.3 Constructed Variables

We constructed a number of variables to support the model estimation. Load and price data were analyzed to define appropriate peak and off-peak periods. The data supported defining the peak during the afternoon hours, between noon and early evening (see Appendix E). Three different peak-period definitions of varying length were tested in the model specification to determine which provided the best fit: noon to 5pm, 1pm to 5pm, and 2pm to 5pm.[36]

Climatic data were used to construct a weather index that included both ambient temperature and relative humidity.[37] These data were also used to sort days into low temperature/low price and high temperature/high price categories, which were used in developing customer baselines in the Load Response Characterization (LRC) model. We

[36] This is a tactic that has proved useful in other similar analyses (Boisvert et al, 2004, forthcoming)
[37] Generally, the humidity factor becomes significant only at temperatures above 70 degrees (F), and its impact is modest (see Appendix E; Attachment C).

also constructed a number of customer-specific categorical variables based on survey responses.

2.7.4 The Constant Elasticity of Substitution (CES) Model

Following well-established conventions, we employed a Constant Elasticity of Substitution model to characterize SC-3A customers' electricity consumption. Most studies of large customer RTP have used this metric (Herriges et al. 1993; Schwarz et al. 2002) or have modeled peak and off-peak electricity as substitutes (Patrick, 1990; Caves et al, 1984; Herriges et al, 1993; Braithwait, 2000).

The CES model is a highly structured and theoretically consistent representation of the trade-offs made by firms that shift production or other business operations from peak to off-peak hours, adjusting electricity usage accordingly, to accommodate the rescheduling of activity in response to peak price changes.[38] We selected the CES model specification because it provides a tractable means for estimating substitution elasticities given time, resource, and data availability constraints. [39] But the CES model approach does impose certain rigidities on assumed customer behavior; most notably that shifting opportunities are limited to the day's peak and off-peak periods and that the elasticity of substitution is constant.

The key characteristics and assumptions of the CES model are as follows:

- The basic assumption is that of *cost minimization* in producing an established level of product or service for which electricity is an input. Thus, we measure *input substitution*, or the substitution of less expensive off-peak power for more expensive peak power. This is in contrast to the more commonly used *own-price elasticity*, which represents the change in consumption of a good (or service) given a change in its price.[40]

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[38] For example, a municipal treatment plant may shut off pumps during high priced hours by either accelerating pumping earlier in the day, making up the water processing later on, or both. Paper plants report building up stocks of storable, intermediate inputs such as wood chips or refined pulp, so that during high priced periods the paper machines can continue to run but total electricity usage is reduced. Cement plants accomplish the same flexibility by storing clinker.

[39] This economic problem involves a three-level profit or cost function, because the underlying production function is assumed to be separable in electricity usage. At the first level of cost minimization, we allocate weekday electricity usage between time periods during the day in which electricity prices differ. The second level involves allocating monthly usage between weekdays and weekends, and the third determines overall electricity expenditures as a proportion of total costs, reflecting the relative demand for electricity in relation to all other inputs in the firm's production process. Given data limitations (lack of data on firm output), we focused only on the first of the three stages of the model: how customers use peak and of-peak electricity to minimize the cost of producing goods and providing services. Doing this requires making the assumption that firm output is constant, but this is unavoidable in the absence of company operating data. (see Appendix E).

[40] The own-price elasticity specification is appropriate for final consumption goods, such as shoes or restaurant meals. Electricity, on the other hand, is an input into a transformation process that produces product that then is sold, or a service that provides comfort, safety or convenience. This is especially true in the context of the operation of a firm or institution.

- The resulting measure of elasticity is defined as the percent change in the ratio of peak to off-peak electricity usage resulting from a one percent change in the ratio of off-peak to peak prices (the "inverse price ratio"). This is referred to as the (input) *substitution elasticity*, to distinguish it from the own-price elasticity of demand.
- Peak and off-peak electricity are assumed to be substitutes, with the level of use of each determined by their relative prices.[41] The total amount of electricity required is determined by the output of the firm, and firm output is assumed to be fixed. However, the total amount of electricity consumed is *not* assumed to be fixed. This is possible because trading off peak and off-peak usage may involve altering production processes, using equipment less (or more) efficiently, requiring more labor, etc., which may result in more or less overall electricity consumption. So long as the net result is to minimize cost, the tradeoff makes sense.
- The substitution elasticity is positive, ranging between zero and infinity.[42]

These assumptions may not fully reflect how some customers actually respond in practice. Alternative, more complex model specifications of customer demand allow shifting of usage to the subsequent day or allow the substitution elasticity to vary with the nominal level of the price change (see Appendix E).

2.7.4.1 Estimating the CES Model

The CES model's general estimating form is as follows:

$$\text{Log (Ratio peak to off-peak usage)} = \text{intercept} + B\text{*Log (ratio of off-peak to peak price)} + C_i\text{* (general effects)} + D_i\text{*(firm effects)} + \text{error term}$$

The estimated parameter, B, is the substitution elasticity. The C_i coefficients represent general effects (such as weather and general market circumstances) that are modeled as dummy variables. The D_i coefficients, also included as dummy variables, quantify "firm" effects, or differences in elasticity among customers based on their characteristics. The firm effects variables are typically constructed from customer survey responses and allow for a more detailed specification of how and why customers respond. To isolate the impact of participation in NYISO DR programs, two dummy variables were constructed: one to represent program participation and a second to indicate the days on which program events were called. The full model derivation and its statistical specification are provided in Appendix E.

One of the goals of this project was to explore the reliability and accuracy of price response estimates based on utility billing and customer information system data, compared to estimates that include additional customer circumstances. If accounting for customer-specific factors did indeed produce better price response estimates, our goal

[41] By contrast, own-price elasticities view peak and off-peak electricity as *complementary* goods.
[42] By contrast, own-price elasticities are negative.

was to specify what data must be collected to support ongoing evaluations of price responsiveness.[43]

We did this by estimating the CES model in two ways. The *Initial* CES model incorporated all customer information that was available without surveying customers. In addition to hourly usage and corresponding SC-3A price data, we used information about each customer's business classification, supply choices (Option 1, Option 2 and competitive supply), and participation in NYISO DR programs as variables. The *Initial* CES model was estimated using 141 customers' usage behavior and characteristics.

The *Final* specification includes variables that were obtained from the customer survey, allowing a more comprehensive picture of the drivers behind customer price response. The tradeoff is that the sample size is much smaller (32 customers), owing to the number of survey respondents (53 customers) and the extent of non-response to various questions. Some variables that turned out to be very important in the final CES model were answered by only a subset of customers.

2.7.5 Load Response Characterization (LRC) Model

The CES model assumes that customers shift electricity-consuming activities from the peak period to the same day's off-peak period. However, many customers reported *curtailing* or *foregoing* discretionary usage during high-priced periods without making it up later (see section 4.2.3). For example, they may shut off plug loads, dim lights, and raise the thermostat setting. The company or institution maintains its output (i.e., the operation of the building to support its occupants' economic activity) by trading off electricity consumption for comfort. In this situation, the estimated elasticity of substitution correctly characterizes the shifting effect, but under-estimates the nominal level of the reduction in peak usage. This occurs because the underlying assumption of the CES model about the relationship between inputs and outputs does not apply in this situation (see Appendix E).

To adjust our characterization of price response to recognize these behaviors, we employed a Load Response Characterization (LRC) Model, adapting a model introduced by Patrick (1990), which distinguishes load shifting from foregoing consumption. The LRC model specifies an empirical relationship between the total daily load change and the change in peak load as follows:

$$\text{Percentage change in total daily usage} = a + \text{Firm effects} + \beta q\ \{\text{percentage change in daily peak usage}\} + \text{error term}$$

A conservation behavior parameter (β_q in the equation) is estimated from customer's hourly electricity usage data to express the degree of foregone consumption relative to a

[43] Gathering customer data through surveys is difficult, particularly in a competitive environment where customers may not be served by the default utility, so it is useful to identify what type of data is necessary to streamline data collection efforts.

customer baseline (CBL).[44] This parameter ranges in value from zero (complete shifting) to one (complete "conservation"), or greater. Values between these extremes indicate combinations of shifting and discretionary peak reductions.

The conservation parameter separates out behaviors that are not fully characterized by the substitution elasticity and allows a more complete picture of aggregate load response than substitution elasticities alone can provide. Most previous analyses of RTP tariffs have not accounted for this phenomenon.[45]

To illustrate, consider the three hypothetical customers in **Table 2-3**. To facilitate comparison, each customer is assumed to have the same baseline usage (40 kWh peak usage and 50 kWh off-peak usage), and each customer reduces peak usage by 50%, or 20 kWh in response to prices. To fully characterize their load response, we examine the relative changes in usage during the off-peak period. In Case 1, the customer shifts usage, kWh for kWh, from peak to off-peak periods. This is characterized as complete load shifting in the LRC model. In Case 2, the customer reduces load in equal proportions during peak and off-peak periods; such behavior is characterized as "conservation" in Patrick's model. In Case 3, the customer reduces peak usage by 50% with no change in off-peak usage. This last case represents a discretionary load curtailment during the peak period only; it is characterized as partial load shifting and partial conservation in the LRC model. Case 3 corresponds most closely to the "foregoing" response that customers could indicate in our survey (see Chapter 4).

We estimated the LRC model for the 32 customers included in the *Final* CES model.

Table 2-3. Treatment of Customer Response Behavior in the LRC Model

Case	Actual Usage (kWh)			Percent Change from CBL			Behavior According to Model	
	Peak	Off-Peak	Entire Day	Peak	Off-Peak	Entire Day	Amount Conserved (kWh)	Amount Shifted (kWh)
1. Shifting	20	70	90	-50%	40%	0%	0	20
2. "Conservation"	20	25	45	-50%	-50%	-50%	20	0
3. Discretionary Curtailment	20	50	70	-50%	0%	-22%	8.9	11.1
All cases are assigned a CBL of: - 40 kWh peak usage - 50 kWh off-peak usage - 90 kWh total over the course of the CBL day								

[44] Patrick labeled this behavior conservation because it involves changing usage in a way more typical of energy-efficiency measures. An alternative interpretation is that peak and off-peak usage are complements, not substitutes as assumed in the CES model, as they are the result of a conservation ethic.

[45] An own-price elasticity specification would address this complementarity, but would still require an adjustment to fully account for how customers respond because it would not capture the substitution effect. In other words peak and off-peak usage cannot be both complements and substitutes in the same demand specifications. Some means of sorting customers *a priori* according to how they respond is needed so that the correct specification can be applied in the correct circumstance. Developing such a mechanism should be a high priority for further research.

2.7.6 Estimating Aggregate DR Potential of SC-3A Customers

Policymakers, load serving entities and ISOs are also interested in estimating the actual amount of peak load that will be reduced, not just the percentage change in peak to off-peak usage. Policymakers need to know the nominal load changes in peak and off-peak periods to evaluate the benefits of implementing price response programs. Load serving entities will want to adjust their market position to account for such load changes, and system schedulers and dispatchers need to know by how much peak demand will decline at various prices so they can adjust unit commitments accordingly.

Once the substitution elasticity is estimated for the CES demand model, it is possible to simulate different levels of demand response over a wide range of price changes. By rearranging the demand equation, it is possible to derive the ratio of peak to off-peak load that would result from the estimated elasticity given a set of expected price and load levels (derived from the CBL calculations for the LRC model) as well as a set of hypothetical prices. The resulting equation is as follows:

$$k_p/k_o = (k^*_p/k^*_o)\ \sigma\ P^* + (k^*_p/k^*_o)$$

where k^*_p and k^*_o represent the peak and off-peak CBL, σ is the estimated elasticity of substitution, and P* is the percentage change in the inverse price ratio. However, without any further assumptions, it is very difficult to derive the actual nominal changes in peak or off-peak load; all that can be known is the ratio of the two.

One way to deal with this would be to hold total load constant across the day. Under this assumption, electricity could be shifted from one period to another, but firms would be restricted from foregoing consumption altogether. This would provide the following estimate for peak load:

$$k_p = (k^*_p + k^*_o)\ \{(k^*_p/k^*_o)\ \sigma\ P^*\ \} + (k^*_p/k^*_o)\}\ /\ [\ \{\ (k^*_p/k^*_o)\ \sigma\ P^* + (k^*_p/k^*_o)\} + 1\ ]$$

However, our survey and LRC results demonstrate that customers do indeed curtail load. By using the results of the LRC model, it is possible to understand how total load in the day would change when prices are higher than normal. The CBL is shifted downwards to reflect the inherent short-term "conservation behavior" that some firms undertake in response to high prices. If the adjusted daily load is then held constant, the shifting associated with the elasticity of substitution model can be simulated relative to this new adjusted CBL (k^{**}_p and k^{**}_o below), thus arriving at a final estimate of peak load (see Appendix E for more detailed explanation).

$$k_p = (k^{**}_p + k^{**}_o)\ \{(k^{**}_p/k^{**}_o)\ \sigma\ P^*\ \} + (k^{**}_p/k^{**}_o)\}\ /\ [\ \{\ (k^{**}_p/k^{**}_o)\ \sigma\ P^* + (k^{**}_p/k^{**}_o)\} + 1\ ]$$

3. Historical Evolution and Market Context for RTP at Niagara Mohawk

It is important to understand the context in which NMPC implemented RTP as the default service tariff for large customers, particularly if one is to draw conclusions about the relevance of findings to other jurisdictions.[46] Factors such as customer characteristics, the availability and attractiveness of alternative service and supply options, and the level and volatility of wholesale day-ahead market prices play important roles in shaping how RTP tariffs are implemented and how much demand response can be expected from customers.

In this chapter, we describe the evolution of rate designs for large customers in the Niagara Mohawk service territory prior to and after restructuring, summarize the key component elements of the SC-3A tariff design and other service and supply alternatives open to customers, and discuss interactions between RTP and the NYISO's Demand Response programs. Information presented in this chapter is drawn from several sources: interviews with NYPSC regulatory staff and customer representatives, review of relevant NYPSC filings and NMPC tariff sheets, and information on tariff subscription provided by NMPC.

3.1 The SC-3A Customer Class

NMPC is located in upstate New York and its service territory includes many of the State's large manufacturing facilities. Since November 1998, NMPC's RTP tariff, known as "SC-3A Retail Choice" (Option 1), is the utility's standard tariff offering to its largest industrial, commercial and institutional sector customers: those customers with metered demand greater than 2 MW, regardless of their business type (referred to as the SC-3A "parent class"). From the early 1980s to November 1998, the default SC-3A tariff was a time-of-use rate. In addition, several alternative rate offerings were also available to customers in the SC-3A parent class. For example, some large customers negotiated individual, long-term contracts with NMPC (SC-11) or were eligible for special economic development rates (SC-12). NMPC also offered two small pilot programs (HIPP and VIPP) during the 1980s and early 1990s that involved variable hourly pricing.

3.2 NMPC's Early Experimentation with RTP and Demand Response

NMPC offered its SC-3A parent class customers two opportunities to participate in voluntary dynamic pricing and DR programs during the 10 years preceding the introduction of retail choice in 1998. The Hourly Integrated Pricing Program (HIPP) was introduced in April 1988 and was the first in the U.S. to subject large customers to hourly-varying prices using two-part RTP (Neenan, 1992). The two-part design hedged each participant's typical hourly energy usage, as defined by the customer baseline load (CBL), at the regular SC-3A time-of-use tariff rates. Deviations in usage from the CBL level were priced at an administratively determined hourly price that reflected the then

[46] NMPC's current SC-3A Option 1 offering is an hourly day-ahead market pricing tariff. Under this tariff, NMPC incurs balancing risk that is effectively born by non-RTP customers through a commodity adjustment charge.

vertically integrated utility's marginal supply costs. Fifteen SC-3A customers signed up for the voluntary RTP experiment, about 10% of eligible customers at the time.[47] After the initial pilot phase, a second recruitment resulted in over 40 participants during the period from 1992 to 1994.

NMPC implemented the Variable Interruptible Pricing Program (VIPP) in 1990 to provide utility system operators with resources that could be dispatched on short notice in response to reserve shortfalls. NMPC purchased demand call options from participants at prices that reflected marginal capacity acquisition costs. When NMPC called the option, customers had the choice of curtailing the prescribed load and receiving a performance-based incentive payment, or purchasing their non-curtailed electricity at the day-ahead "market" price.[48] VIPP replaced earlier interruptible rates that provided reduced demand charges in return for the right to interrupt customers in emergencies. In effect, VIPP was HIPP service but restricted to times when system conditions warranted, regardless of the prevailing day-ahead prices.

Customers' experiences with the HIPP and VIPP pilots facilitated the subsequent adoption of RTP as the default service tariff in three ways. First, customer experience with these programs was largely positive. Customers who had experienced RTP at a time when prices were quite low thought that the RTP tariff would be a way to save money compared to the otherwise applicable tariff. Second, HIPP and VIPP developed familiarity among customers with the notion that electricity costs vary on an hourly time scale and with how to monitor and respond to price signals. Third, these experiences provided a framework for developing individually negotiated contracts with customers during the period 1995-98, providing a vehicle for customizing the service to customers' specific needs and hedging preferences.[49] This direct experience, in which almost a third of the SC-3A customers participated in some manner, raised awareness among all customers and was likely an important factor in customer acceptance of RTP during the regulatory proceedings in 1998.

3.3 Retail Access and Adoption of RTP as the Default Service Tariff for SC-3A Customers

The current SC-3A tariff design fully unbundles commodity and wires services and was adopted as part of Niagara Mohawk's general rate case, known as "Power Choice" and a NYPSC decision that approved a restructuring settlement agreement between NMPC and various parties in 1998. In New York, restructuring was implemented separately for each utility (not statewide, as was the case in California). An earlier proceeding had established class-level revenue and stranded cost allocations – it remained to design rates to allocate these costs among customers.

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[47] Of the 15 volunteers, nine were placed on RTP in April 1988 – the rest were assigned to a control group and were retained on the default SC-3A time-of-use tariff until April 1989, at which time they began RTP service.
[48] The VIPP pilot was eventually abandoned when marginal prices became so low that the necessary curtailment incentive was not achieved.
[49] During that period, although the HIPP SC-8 service was not available, NMPC used the RTP framework for negotiating contracts to forestall uneconomic bypass from on-site cogeneration.

RTP was proposed by Niagara Mohawk and was largely uncontested. The position of various parties involved in Niagara Mohawk's rate case – the utility, customer representatives, and regulatory staff – was shaped by their expectations about future wholesale and retail markets (see **Table 3-1)**. Just prior to restructuring, Niagara Mohawk had excess generating capacity so competitive market commodity prices were expected by most to be low for a number of years. Many parties believed that a vibrant retail energy services market would develop in New York to provide customers with a wide range of product and service offerings, including fixed rate products and financial hedging services that would shield customers that did not wish to be exposed to day-ahead or real-time spot market price volatility. Facilitating demand response was not an explicit policy goal of regulatory staff in 1998, in part because the need for it was not yet realized.

Table 3-1. Expectations and Goals for RTP in 1998

Stakeholder	Expectations	RTP Goals
Niagara Mohawk	• Continued excess generating capacity and high reserve margins	• Pass through wholesale market commodity prices (and price risk) to large customers • Divest generation
Large Customer Representatives	• Low prices • Vibrant retail energy services market	• Access transparent market prices • Lower electricity costs
NYPSC Staff	• Continued excess generating capacity • Customers are "big boys" • Vibrant retail energy services market	• Encourage retail market development • Promote economically efficient rate designs

Niagara Mohawk was primarily interested in promoting RTP for large customers as a way to manage its wholesale market price risk. The company was also divesting many of its generation assets as part of the transition to a competitive wholesale market. The amount of load left un-served after these planned divestitures roughly matched the combined load of the SC-3A class. Consequently, the utility saw RTP as a convenient way to alleviate much of its wholesale price risk by passing that risk on to its customers. By pricing unbundled commodity service at the NYISO's day-ahead price, its risk is limited to the day-ahead/real-time market spread.[50] Moreover, if customers reduce usage in response to high day-ahead prices, NMPC's risk is further abated.[51] Niagara Mohawk also did not believe that RTP tariffs for SC-3A customers would impose significant incremental costs to the utility, because customers already had hourly interval meters, a major overhaul of the billing system was already underway in order to accommodate retail competition, and marketing and customer education costs were expected to be relatively low because of the default nature of the tariff.

[50] This difference flows through to other customers through the CAC and is therefore not a risk borne by the company

[51] Because NMPC quotes all-use hourly prices indexed to NYISO day-ahead prices, the utility holds price risk on variations in usage from the level it procures in the day-ahead market. This difference flows through to other non-SC-3A customers through the CAC and is therefore not a risk borne by the company

Multiple Interveners, representing large industrial and commercial electric customers, supported RTP because they expected that wholesale market prices would be low for those customers that remained on the tariff and because many of their member companies planned to switch and contract with competitive ESCos for retail commodity service. At the time, the large industrial customer group in New York was convinced by the arguments of restructuring proponents that competitive markets would provide electricity at lower cost than regulated utilities had done; thus they supported retail competition and thought that day-ahead market prices would remain low.

Staff at the NYPSC were receptive to RTP as the default service tariff for SC-3A customers because the rates reflected the marginal costs of providing power (it was an economically efficient rate design) and because they believed that these large customers were sophisticated enough to make informed energy supply decisions in a competitive retail market environment. Furthermore, NYPSC staff expected competitive marketers would offer alternatives to RTP and as such did not consider this implementation to be truly "mandatory". The SC-3A tariff design issues were also relatively easy for the NYPSC to ratify because the parties had reached a settlement agreement on this issue.

3.4 SC-3A Tariff Design

The SC-3A rate schedule adopted with retail access in 1998 is unbundled; electric commodity is separated from the recovery of other costs, such as transmission, distribution and competitive transition charges (CTC). The non-commodity portions of the tariff apply to all customers in the SC-3A class, whether they take commodity service from Niagara Mohawk or from a competitive supplier.

Customers taking commodity service from Niagara Mohawk had two options in the fall of 1998. Option 1 was and remains the default service applicable to customers that do not find an alternative commodity provider. Option 2 was an alternative, hedged standard offer that was made available to customers on a one-time election basis just prior to the implementation of retail competition in 1998. Customers that elected this option received a fixed commodity rate on a take-or-pay contract quantity that they nominated for a five-year period. **Table 3-2** and the following sections provide additional details on the tariff components for SC-3A Options 1 and 2.

3.4.1 Option 1

Under Option 1, a customer's electric commodity charges are derived from NYISO DAM prices. NMPC posts, by mid-afternoon the day prior to their going into effect, prices indexed to the NYISO day-ahead market (DAM) prices (which are posted at noon).[52] This means that the customer's actual metered hourly load served under Option 1 is subjected to the corresponding hourly price – there is no customer baseline load (CBL) or other provision that would protect customers from price variability. Customers receive prices by consulting a web site that displays the next day's hourly prices by 4pm each

[52] Customers that eschewed the Option 2 alternative and did not contract with another entity for commodity service when the retail market opened in 1998 were placed on Option 1 by NMPC.

day.[53] The final SC-3A prices also include a markup to the NYISO posted prices to cover real-time market settlement costs that apply to all retail loads. For the purposes of this tariff, these day-ahead market prices are final, and apply to all usage. The NYISO employs locational-based marginal pricing (LBMP)[54], so the RTP prices paid by individual SC-3A customers depend on the load zone in which they are located as well as their delivery voltage level. Niagara Mohawk applies an adder to the NYISO prices that recovers NYISO ancillary service costs and line losses.

Table 3-2. Comparison of Option 1 & 2 Tariff Components

Unbundled Tariff Components	**Basis for Charge Determination**	
	Option 1	**Option 2**
Electric Commodity	NYISO day ahead hourly market indexed prices – depend on delivery voltage and load zone	Fixed rates for on-peak and off-peak nominated loads – depend on delivery voltage and load zone
Non-Commodity Charges:		
Distribution Delivery	• Flat Customer fee • $/kW* • ¢/kWh charges for primary voltage customers only (since 2/1/02)	• Flat Customer fee • $/kW* applied to nominated loads
CTC	• $/kW** demand charges • variable-block pricing *charges depend on delivery voltage, load zone*	• $/kW** applied to nominated loads charges depend on delivery voltage and load zone fixed in contract
Reactive Power	$/ billed rkVA	

*Customer peak demand (kW) is defined by customers' highest metered 15-minute demand during each billing period. There is no demand ratchet.
** Customer peak demand (kW) is defined by customers' highest on-peak metered 15-minute demand during each billing period. There is no demand ratchet

3.4.2 Option 2

NMPC also offered customers a fixed price, standard offer service in which they could elect to nominate all or a portion of their load for up to a five-year period.[55] Customers choosing this option had to so indicate prior to October 1, 1998 for the five-year period beginning November 1 of that year. Representatives of large customer groups supported the concept of a fixed-rate tariff alternative. In designing Option 2 rates, NMPC forecast electricity market prices for the next five years, including a risk premium; the rate was designed to be neither more nor less attractive than Option 1.

[53] The website, with historical RTP prices by load zone and delivery voltage level, is available at: http://www.niagaramohawk.com/youracct/priceenrg/essapps/price_select.asp
[54] LBMP is a system of pricing in which transmission capacity constraints are internalized into market prices by defining load zones with distinct market clearing prices. Niagara Mohawk's service territory spans six NYISO load zones: West, Genesee, Central, North, Mohawk Valley and Capital.
[55] Option 2 was designed to be in effect only during the transition period, which was set equal to the five-year period of the Power Choice Settlement Agreement.

Customers that elected Option 2 were required to nominate monthly peak and off-peak demand blocks (at 100% load factor) for up to five years *when they signed the contract*. If desired, they could nominate no load in certain periods. Indeed, several customers chose to nominate some or all of their loads for only the first few years. These nominations could not be changed once the contract was signed – if the customer used less than its contracted demand, take-or-pay provisions required purchase of all subscribed power and prohibited its resale. However, the customer could elect initially to sign up for a somewhat higher rate under Option 2, which gave them the option to terminate the Option 2 contract with six months' notice.[56]

About 18% of SC-3A customers ultimately elected to nominate all or a portion of their load for the Option 2 tariff service. In our interviews with NYPSC staff and industrial customer representatives, we asked them about their expectations for participation levels in Option 2 vs. Option 1. They acknowledged that subscription rates for Option 2 were relatively low, though not surprisingly so, given the relatively restrictive terms and conditions of the Option 2 service contract and customers' uncertainties about the types of offers they would receive from competitive retail suppliers. The Option 2 contracts expired in August 2003 and they are not being renewed by NMPC. Thus, as contracts ended, customers that were on SC-3A Option 2 were placed on the default service option (Option 1) until such time as they make competitive supply arrangements.

3.4.3 Non-Commodity Tariff Components

A key design feature of the SC-3A rate is the unbundling of the tariff components. The non-commodity portions of the SC-3A rate (see Table 3-2) apply to all SC-3A customers, whether they take service on Option 1, Option 2, or from a competitive supplier. The unbundled RTP tariff design provides a mechanism for NMPC to recover its non-commodity costs (e.g., transmission, distribution, and customer costs) from retail access customers. From the utility's perspective, it also addresses concerns about potential under-recovery of non-commodity fixed costs in one-part RTP tariffs (see, for example, O'Sheasy, 2002). These costs are recovered in a blended rate that is dependent not only on the customer's volumetric usage (kWh), but also on its monthly peak demand (kW). From the customer's perspective, the unbundled RTP tariff means that the commodity portion of bills varies with market prices, while the non-commodity rates are known in advance and depend primarily on their peak demand and usage levels.

The CTC portion of the rate is meant to recover SC-3A customers' share of Niagara Mohawk's "stranded debts", which were negotiated and agreed to as part of the NYPSC decisions on restructuring. This rate component will eventually be retired when the established revenue target has been met. Option 1 and 2 customers were expected to bear equal burden for the CTC.

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[56] Potential reasons customers may have wanted the option to terminate their Option 2 contracts include the possibility of finding a better deal from a competitive supplier or customer uncertainty about their own future production levels.

3.5 Other Supply and Service Options

3.5.1 Competitive Market

Since the introduction of retail choice in 1998, SC-3A customers also have had the option of purchasing electric commodity service from a competitive retail supplier. This option is available to customers regardless of whether they chose to nominate some of their load under Option 2. If the customer did make Option 2 nominations, the balance of their power could be taken from a competitive retail supplier – termed an ESCo (energy service company). The unbundling of SC-3A service, described in the previous section, was intended to facilitate customer switching for the commodity portion of their electric bills.

In order to encourage the development of a competitive retail electricity market, the NYPSC approved a "customer service back-out credit" which allows retailers to offer commodity to customers at a discount of approximately two mils/kWh relative to utility service. In theory, this discount reflects commodity-related procurement and customer service costs that are avoided by NMPC.[57] In addition, customers taking service from an ESCo receive some additional benefits by avoiding taxes on electric commodity delivery service, which provide a discount that can be shared with customers that switch (McDonough, 2004).

Based on interviews with NYPSC staff, representatives of industrial customers, and results of our customer survey, it appears that the initial expectations of a vibrant and robust retail electricity market have not (yet) been realized in Niagara Mohawk's service territory. There has been a substantial shakeout in the number of active ESCos and many customers are not particularly satisfied with the range (or pricing) of retailer service offerings, particularly the implicit premiums quoted by ESCos for hedged products. It appears that the most common product now offered by ESCos is a contract that offers prices that are discounted and indexed to SC-3A Option 1 prices, whereby customer savings come primarily from the customer service back-out credit and avoided taxes. The implication is that the majority of customers that have switched to ESCos are still exposed to RTP for their commodity service.

NMPC customers also had the option of taking the standard offer service (Option 1) and entering into a financial hedge with a financial services provider or ESCo that would eliminate or reduce NYISO day-ahead market price volatility. Such products may include financial swaps, price collars or caps, or other customized hedging products. Based on results from our customer survey, it appears that about 10-20% of SC-3A customers have sought out and signed agreements for financial hedging products during the last five years.

[57] The customer service back-out credit was a negotiated amount set in 1998 at the estimated level of avoided costs, with provisions for subsequent adjustment to account for actual avoided costs. A regulatory proceeding is currently examining this issue for all of New York's utilities.

3.5.2 Individually Negotiated and Special Contracts

About 25% of customers with peak demand greater than 2 MW (and who thus meet the SC-3A parent class definition) take service on other rates or individually negotiated or special contracts offered by Niagara Mohawk. **Table 3-3** summarizes the number of customers on each tariff or contract option and their aggregate summer peak demand (McDonough, 2003). Customers on SC-4 tariffs and individually negotiated or special contracts (SC-11 and SC-12 respectively) have not been included in this study for various reasons.[58] For the purposes of this study, we consider them a separate population from SC-3A customers. It is worth noting that these customers tend to be among the largest customers served by the utility, as evidenced by the fact that the 68 customers on alternate rates have an aggregate summer peak demand of about ~723 MW. In this section we describe these various rates and provide an overview of their associated populations for background purposes only.

Table 3-3. 2003 Rate Classification of Niagara Mohawk's Large Customers (Peak Demand >2MW)

Service Classification	Description	Number of Accounts	Summer Peak Demand (MW)
SC-3A	Default classification – includes Option 1, Option 2 and competitive supply	204*	721
SC-4	Untransformed Service to Customers Taking Power from Projects of the New York Power Authority	15	320
SC-11	Individually Negotiated Contract Rates offered prior to 1998	39	241
SC-12	Standard Discount and Individually negotiated Contracts offered since September 1998	10	89
Total SC-3A Parent Class		**268**	**1,371**

* Of these 204 accounts, 149 accounts did not have NYPA allocations and were thus included in the target population for this study, per the NDA negotiated with NMPC. Among this group of 149 accounts, some take commodity service from NMPC while the rest take commodity service from ESCos.

SC-4 is a tariff offered to customers that qualify for New York Power Authority (NYPA) allocations[59] in the Niagara area and that take supplemental power from Niagara Mohawk at transmission level voltage. Customers typically receive part of their energy requirements from NYPA at rates that are fixed, or that vary only periodically, rather than daily. If consumption exceeds the NYPA allocation, the customer pays SC-4 tariff rates

[58] SC-11 service is for customers that, prior to 1998, signed an individually negotiated contract for service with NMPC, the purpose of which was to avoid uneconomic bypass. SC-12 serves that role under Power Choice[SM], and for customers that receive economic development power allocations from the New York Power Authority.

[59] NYPA contracts provide low-cost hydropower to customers under economic development rationale. In addition to the Niagara area contracts, NYPA allocations may be granted in other regions under the Economic Development Power (EDP) and Power for Jobs (PFJ) programs.

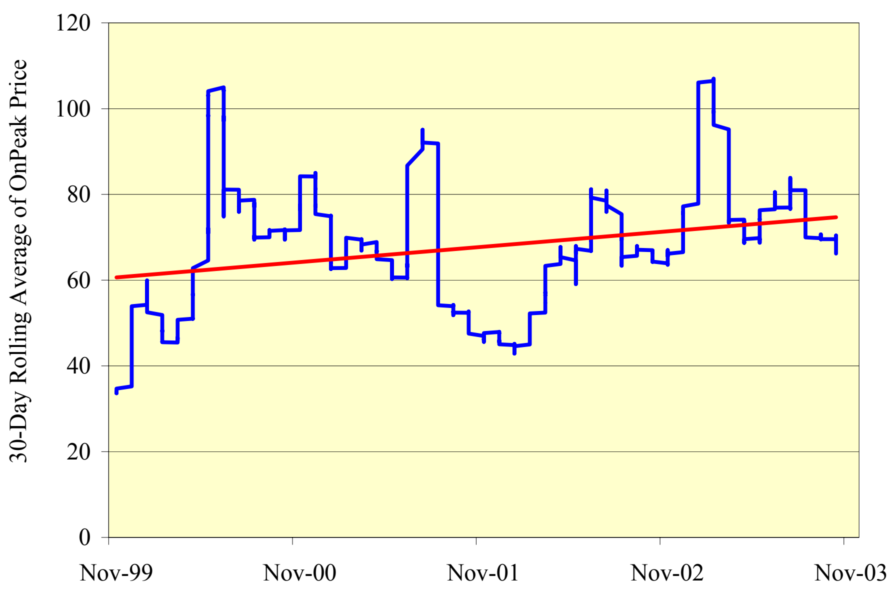
for demand and energy allocated to NMPC.[60] The SC-4 rates are equivalent to those for the customer's parent class (i.e., SC-3A). Thus the 15 SC-4 customers are de facto partially hedged and pay SC-3A Option 1 (RTP) prices for their marginal power requirements.

The SC-11 service classification includes customers that individually negotiated contracts with NMPC. Nearly all of these contracts were negotiated in the mid-1990s and involved rate discounts motivated by the threat of bypass and/or self-generation. As part of the restructuring agreement, the NYPSC allowed NMPC to extend these previously negotiated contracts for the five-year settlement period covered by the Power Choice rate case. SC-12 discount contracts are offered to customers that who demonstrate to NMPC's satisfaction that they have a contestable alternative for their existing or prospective load. Many customers who take service under the SC-11 and SC-12 tariff contracts and who take commodity service from NMPC are billed for commodity at the NYISO DAM price. All of these contracts discount the delivery portion of the rate, while some older contracts contain fixed rate commodity provisions.

3.6 Trends in SC-3A (Option 1) Prices

To provide context for assessing customers' reactions to the implementation of RTP as their default service tariff, it is useful to examine the SC-3A prices they have faced over the past four years since the NYISO day-ahead market was established.

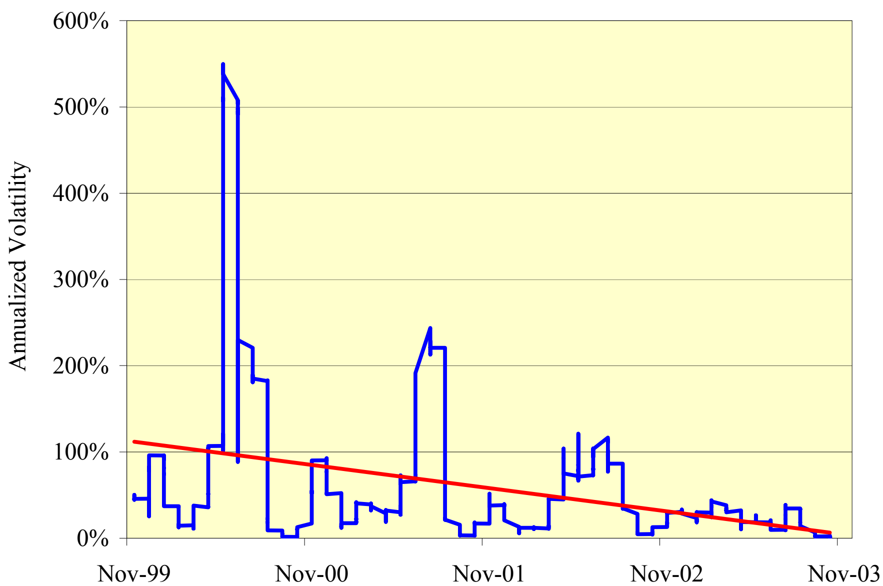
Figure 3-1. Trends in Average Capital Zone Peak RTP Prices (2000-2003)



[60] The SC-4 tariff uses a load-factor sharing formula, which employs the ratio of the NYPA allocation (in kW) to the metered monthly maximum demand, to determine how much energy usage is billed to NYPA versus NMPC supplied energy.

Two important trends are noteworthy in this time period: *average* commodity prices have increased, while the *volatility* of prices has decreased. These trends are illustrated in **Figure 3-1**, which plots average peak period SC-3A prices for the Capital region, and **Figure 3-2**, which plots a standard measure of volatility – an annualized 30-day rolling average of the ratio of peak prices on subsequent days, also for the Capital zone.[61] While there are some regional variations, these general trends hold true for prices in all load zones in which SC-3A Option 1 customers are located, and can be attributed in part to the NYISO's efforts over this period to mitigate price spikes. Several major market rule changes have succeeded in reducing price volatility but may have contributed to an overall increase in average prices. So although high prices have become less frequent and price volatility has decreased, the average prices seen by SC-3A customers have increased over time.

Figure 3-2. Trends in Volatility of Capital Zone Peak RTP Prices (2000-2003)



Regional variation in SC-3A prices is manifested in differences between the Capital load zone and the other five SC-3A load zones, which are located in western upstate New York and are sometimes referred to as the Western New York "super-zone". Prices are frequently higher in the Capital region than in other parts of NMPC's service territory due to transmission congestion along the Central East interface. When this interface is constrained, cheaper electricity from the western part of the state is not able to flow east along the transmission system; higher priced generators then are dispatched to produce power to meet the needs of consumers in the Capital zone. Wholesale market prices in the other five zones tend to move together and during congested periods can deviate significantly from those in the Capital zone.[62] In **Table 3-4**, we illustrate these regional differences by comparing Capital zone average on-peak and off-peak weekday price and

[61] In both figures, the peak period is defined as 7am to 11pm, and the prices are for primary voltage customers.
[62] The Capital zone is located in NYISO load zone F. The other NMPC load zones are located in NYISO load zones A through D.

volatility data against the Central region, which is representative of the Western NY super-zone.[63]

Table 3-4. Trends in SC-3A Commodity Prices (2000-2003)

Region	2000		2001		2002		2003	
	on-peak	off-peak	on-peak	off-peak	on-peak	off-peak	on-peak	off-peak
	Average Price ($/MWh)							
Capital	68.44	33.26	65.22	34.83	63.03	35.40	77.65	47.74
Central	54.98	30.39	58.89	32.50	54.84	32.24	71.93	44.07
	Annualized 30-Day Rolling Volatility							
Capital	111%	79%	43%	20%	34%	27%	17%	23%
Central	68%	54%	38%	20%	26%	20%	16%	22%

Note: On-peak is defined as the period from 7am – 11pm and off-peak is defined as the period from 11pm to 7am. All prices are for weekdays only.

In 2003, average on-peak prices in the two zones were in the range of $72-78/MWh, while off-peak prices averaged $44-47/MWh. Average prices during on-peak hours were about 8-20% higher in the Capital region than the Central region (depending on the year), while off-peak prices were about 10% higher. Average on-peak prices have increased by 31% and 13% in the Central and Capital regions respectively over the last four years. These increases have been far from steady – average on-peak prices rose in 2001 and then fell back to 2000 levels or lower in 2002. Average off-peak prices rose about 2-5% per year between 2000-2002, followed by a dramatic 35% increase in 2003.

The standard measure of volatility presented in Figure 3-2 and Table 3-4 is calculated using a time series of daily average on-peak and off-peak prices (Clewlow and Strickland, 2000). The basis for the calculation is the "daily return", which is defined as:

$$\frac{P_{avg}(t) - P_{avg}(t-1)}{P_{avg}(t-1)}$$

where $P_{avg}(t)$ is the average price on a given day, and $P_{avg}(t-1)$ is the average price on the preceding day. A 30-day rolling volatility is computed for each day of the year by taking the standard deviation of the daily returns for the 30 consecutive days surrounding it, starting from the 15th weekday preceding the day in consideration.[64] Finally, the resulting annualized volatility time series (elements of which are 30-day rolling annualized volatilities for each weekday) is averaged over the year – these are the values presented. We did this separately for on-peak and off-peak periods.

In 2000, it is clear that prices (both on-peak and off-peak) were very volatile in the Capital region (111% and 79% respectively). Off-peak volatility in this region dropped to the 20% level in 2001 and stayed in that range, while on-peak volatility sank more

[63] Weekends are not considered in this table. We used prices for primary power delivery; secondary delivery charges follow the same trends.

[64] These daily 30-day rolling volatilities are then annualized by multiplying them by the square root of 255 (the number of weekdays in a year).

gradually to 17% in 2003. The Central region also experienced its highest price volatility in 2000, though not as high as the Capital Region (which, as noted, is transmission constrained). From 2001 to 2003, price volatility was similar in the two regions.

3.7 Participation in NYISO Demand Response Programs

As wholesale and retail markets in New York have been restructured, the NYISO and state regulators have increasingly recognized the importance of price-responsive load in mitigating shortfalls in system reserves and dampening price spikes in day-ahead and real-time markets. Beginning in 2000, the NYISO has implemented several pay-for-performance demand response programs to facilitate customer load participation in wholesale markets: (1) the Emergency Demand Response Program (EDRP), (2) the Day-Ahead Demand Response Program (DADRP), and (3) a capacity call option program, the Installed Capacity Special Case Resources (ICAP/SCR).

EDRP and ICAP/SCR are emergency DR programs that provide mechanisms where demand can be reduced on short notice when reserve shortfalls are forecast. EDRP is a voluntary emergency program that pays customers the greater of $500/MWh or the prevailing real-time market price for curtailments of at least four hours long when called by the NYISO. There are no penalties for enrolled participants that fail to curtail. The ICAP/SCR program allows customers that meet certification requirements to offer unforced capacity (UCAP) to Load Serving Entities (LSEs) and to the six-month strip and the monthly reconfiguration auctions that are administered by the NYISO. Participants are obligated to curtail when called with two or more hours' notice, provided that they were notified the day ahead of the possibility of such a call. Failure to curtail can result in penalties that exceed the amount of the initial ICAP payment received.

DADRP is an economic program that allows customers to submit load curtailment bids into the day-ahead market (DAM). Bids are treated as generation resources. If scheduled, the participant is paid the DAM clearing price for curtailed load relative to a customer baseline. However, if the customer has a shortfall in its scheduled curtailment, it must buy it at the higher of the DAM price at which the curtailment was scheduled or the real-time market price. When a customer's bid is accepted, the NYISO adjusts downward, by a corresponding amount, the day-ahead obligation of the LSE that serves the customer, thereby ensuring that it does not lose or gain from the transaction.[65]

Table 3-5 provides statewide information on the number of participating customers and enrolled curtailable load in the three NYISO DR Programs during 2003. For the two consecutive days on which EDRP and ICAP/SCR were called in 2003 (August 15 and 16), load curtailments from the two programs combined were ~8-900 MW and ~4-500 MW respectively. About 16,400 MWh of load was actually curtailed over the 28 hours

[65] Opponents of DADRP refer to the customer payment as a double payment, arguing that it should be satisfied with the bill savings it realizes, and the LSE payment as a subsidy. The first assumes that customers incur no costs to curtail, and the latter ignores the fact that the curtailments can produce price reduction benefits that are larger than the subsidies, and inure to all stakeholders (Neenan et al, 2003; Boisvert and Neenan, 2003).

that the program events were called during these two days. The actual amount of load curtailed is far lower than enrollment levels would suggest in the DADRP program. For example, scheduled bids in the DADRP program totaled 1752 MWh in 2003, which amounts to approximately 10 MW on any particular day. This is much lower than the potential ~410 MW enrolled in the program.

Table 3-5. Statewide Participation in NYISO Demand Response Programs: 2003

Program	Number of Customers	Enrolled Curtailable Load (MW)	Actual Load Curtailed (MWh)
EDRP	1,323	854	7,828
ICAP/SCR	213	850	8,634
DADRP	27	411	1,752

Source: NYISO (2003)

NMPC SC-3A customers are eligible to participate in NYISO DR programs, and about 25% do.[66] The interaction between RTP default service tariff and the NYISO DR programs raise important policy and program design issues as to optimal strategies to stimulate demand response. For example, given the relatively high participation rates and observed load curtailments in EDRP and ICAP/SCR, was there some aspect of the NYISO DR programs that made responding to market prices feasible or profitable? Should customers on Option 1 who are exposed to hourly day-ahead market prices, also be allowed to participate in economic ISO DR programs (DADRP)?

[66] NYISO DR program participation by SC-3A customers is described in sections 4.1.1 and 4.3.6.

4. Customer Characteristics and Choices

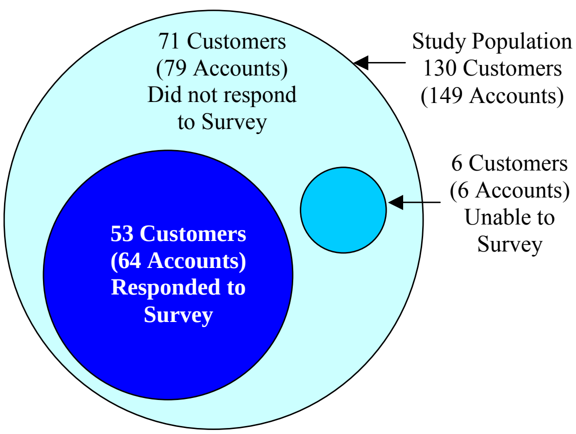
In this chapter, we summarize results of the customer survey and follow-up telephone interviews, examining correlations of factors in a "top-end" analysis.[67] We begin by comparing the business and facility characteristics of survey respondents to the target population of SC-3A customers to address the issue of sampling bias. We then summarize customers' attitudes towards the SC-3A RTP tariff design and implementation and how they respond to dynamic prices. A variety of choices that were available to customers are then examined: whether to choose an alternative supplier, whether to fully hedge against price and volume risk, whether to partially hedge using supply options or financial hedging products, and whether to participate in NYISO demand response programs.

4.1 Who are SC-3A Customers?

4.1.1 Target Population, Survey Respondents and Sampling Bias

The SC-3A study population provided by NMPC consists of 149 billing accounts held by 130 customers.[68] Six of the 130 customers indicated to NMPC customer representatives that they wished to be excluded from the survey and were therefore not contacted – the remaining 124 customers were invited to participate. In all, 53 customers representing 64 accounts responded (see **Figure 4-1)**. The 53 responses comprise 42% of the population by account, and 40% of the customers. Geographically, the survey respondents are fairly evenly distributed across the six zones covered by NMPC's service territory.

Figure 4-1. Customers and Accounts in the SC-3A Study Population



The 2003 Northeast Blackout occurred ten days into the survey period. The blackout initially hampered survey response due to lost workdays. However, it may have ultimately enhanced customer response by bringing electric system reliability concerns to bear. We did not attempt to formally monitor or account for response bias in conducting

[67] Wherever we indicate relationships between factors, we apply a "Chi-squared" test to determine if the dependence is statistically significant.
[68] Thirteen SC-3A customers hold more than one account: nine customers each have two accounts; two customers have three accounts each, and two customers each had four accounts.

the survey, but we do compare several observable characteristics of survey respondents to the study population: business type, load characteristics, basic supply choice, and enrollment in NYISO DR programs. The results are summarized in **Table 4-1** and discussed below.

Table 4-1. Characteristics of Survey Respondents Compared to the Study Population

Characteristic		Survey Respondents (N=53 customers, 64 accounts)	Study Population (N=130 customers, 149 accounts)
Business Type	Industrial	40%	32%
	Commercial	21%	23%
	Government/education	40%	46%
Load Characteristics	Average Annual Load	17,312 MWh	19,377 MWh
	Average Monthly Peak Demand	3.0 MW	3.4 MW
*Basic Supply Choices**	Option 2 Nominees	9%	18%
	Competitive Supplier	52%	53%
DR Program Enrollment	EDRP	38%	28%
	ICAP/SCR	13%	9%
	DADRP	4%	1%

*Tariff information on supply choices was not available for 5 customers, 3 of whom were survey respondents.

Business type. We defined three business types that allow comparisons across sectors: industrial, commercial and government/education.[69] Industrial customers include primary and secondary manufacturing industries. Commercial customers include facilities such as retail space, office buildings, hospitals, health care facilities, and large multi-family complexes. The government/education category includes local, state, and federal government facilities, universities, schools, and other like organizations that share an institutional decision-making structure. We use these categories throughout our study to compare various aspects of customer response to RTP.

The proportion of commercial customers that responded to the survey is similar to their representation in the study population (Table 4-1). However, industrial customers are somewhat over-represented in the survey sample and government/education customers are under-represented.

Load characteristics. On average, survey respondents use about 10% less electricity than the study population.[70]

Basic Supply Choices. Survey respondents were less likely than non-respondents to have selected Option 2 (see Table 4-1). This could indicate that survey respondents were more willing to expose themselves to price variability.

[69] Business type categories were determined using two-digit SIC codes.
[70] Averages were calculated using available hourly interval metered data for 2001-2002.

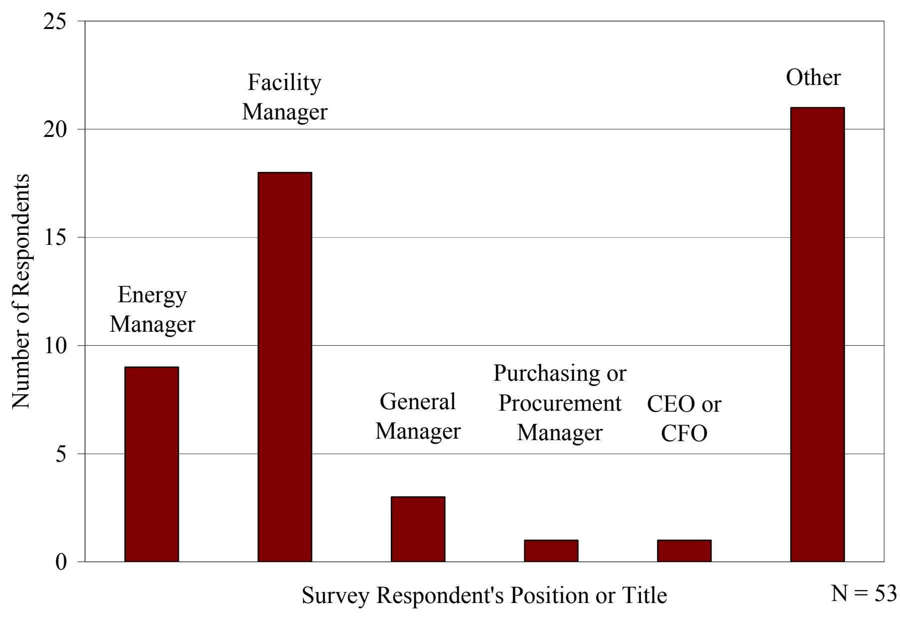
Demand response program enrollment. Of the three DR programs offered by NYISO, EDRP has the most significant enrollment by SC-3A customers (38%). Survey respondents were 30-40% more likely to enroll in EDRP and ICAP/SCR programs than the study population. Thus, survey respondents may be somewhat more interested in or willing to curtail load in response to ISO system emergencies than the study population as a whole.

While the comparisons above do not rule out the possibility of response bias, overall, the differences between survey respondents and the study population do not appear to be dramatic. As a whole, the sample respondents match the population moderately well in terms of basic firm characteristics and customer choices.[71]

4.1.2 Position of Survey Respondents

NMPC provided us, from their account records, with the key account contact person for each customer facility or the individual responsible for making decisions about energy within each organization. We asked survey respondents to indicate their title or position in order to better understand the position and responsibilities of these individuals within their organization. As shown in **Figure 4-2**, 51% of the respondents were energy or facility managers (N=53), and another 34% indicated "other" positions, mainly plant- or energy-related engineering or directorship titles.

Figure 4-2. Position of Individuals Answering Survey



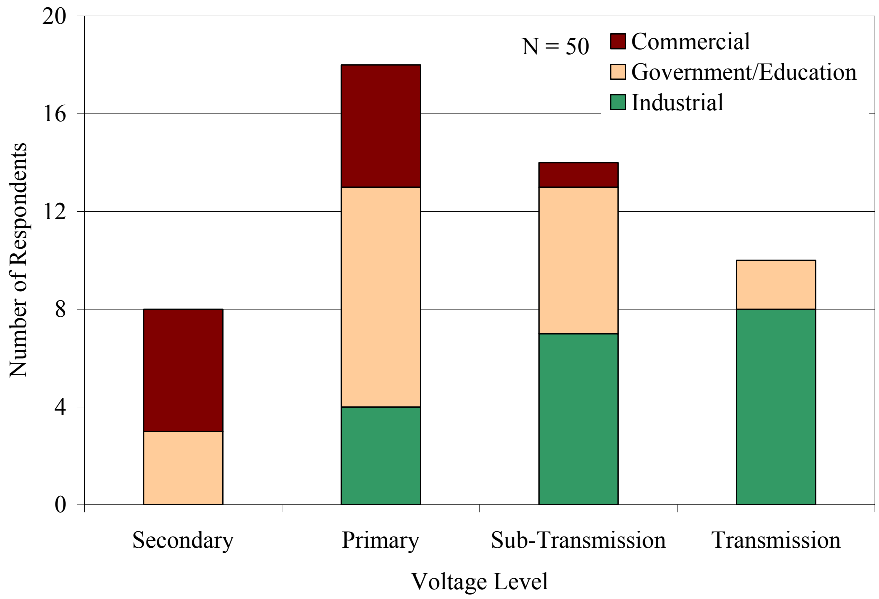
[71] Nevertheless, survey respondents are by definition "special", having self-selected themselves into the respondent pool. There is no statistical resolution to these issues, which should be kept in mind when reflecting on the relevance of extrapolating results from the surveyed customers relative to the NMPC SC-3A customer class as a whole (or to potential RTP customers in other states).

4.1.3 Characteristics of Firms and Organizations

In this section, we look in greater detail at customers' facility, business, and electric usage characteristics based on survey results. We identify a number of customer attributes that might influence their choices regarding commodity suppliers, interest in hedging against price volatility, and participation in DR programs.

The delivery voltage levels of survey respondents are shown in **Figure 4-3**. The industrial customers in our survey tend to take power at higher voltage levels than government/education and commercial customers.

Figure 4-3. Delivery Voltage Level of Survey Respondents by Type of Business



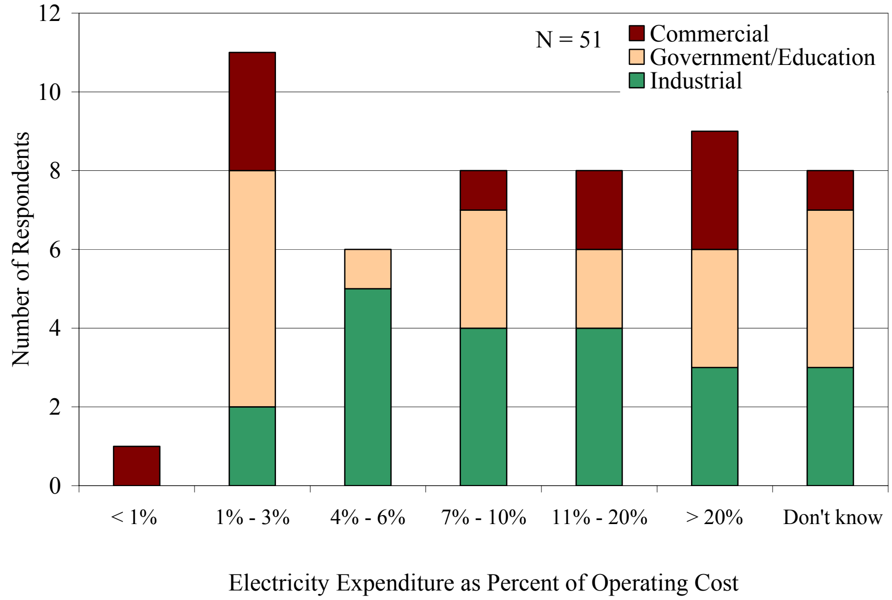
We asked survey participants to estimate the share of their facilities' total annual operating costs made up of electricity expenses.[72] The median response was 7-10%, although 18% of respondents indicated that electricity costs account for more than 20% of their facilities' total annual operating costs (see **Figure 4-4**). Overall, the respondents report higher values than expected, although we observe the full range of responses among the three customer business types. Other research on large customers in New York State also reveals quite high answers to a similar question (Neenan et al, 2003).[73] Whether or not the question was answered or interpreted correctly, the observed responses do reveal that the *perception* of the individuals responsible for making

[72] Respondents were asked to choose from the following options: less than 1%, 1-3%, 4-6%, 7-10%, 11-20%, greater than 20%, and "don't know".

[73] Neenan et al (2003), in a survey of large customers in New York state, asked virtually the same question (though different responses were offered, the largest being >10%) and found a wide variation in electricity costs, with a median response of 5% and 25% of responses greater than 10%. It could be that some respondents answer relative to the facility *energy bill* with which they are familiar, rather than total operating costs.

decisions about electricity is that these costs are significant. It is reasonable to expect that this perception might impact their choices.

Figure 4-4. Importance of Electricity Expenditures on Facility Operating Expenses



We asked customers to indicate how much their electricity usage fluctuates, due to hot weather, in percentage terms relative to an "average summer day"(see **Figure 4-5**). Commercial customers in particular appear to be quite temperature sensitive – 73% indicated fluctuations greater than 7%. This is not surprising as commercial facility loads tend to be dominated by space conditioning. Government/education sector respondents also indicated relatively high temperature sensitivity – 44% indicated fluctuations greater than 7%. Industrial facility respondents' loads appear relatively insensitive to temperature changes (only 30% with fluctuations >7%), reflecting the predominance of process-driven electric loads.[74]

We also asked about customers' load profiles. We asked them to rank electricity usage from highest to lowest during four time periods: morning (8am to 12pm), afternoon (12pm to 5pm), evening (5pm to 10pm), and night (10pm to 8am).[75] **Figure 4-6** plots the time of day assigned highest usage by each customer.[76] Not surprisingly, we see that the majority of customers report peak usage during the day, and that morning and afternoon usage is of roughly equal importance. A few customers from each of the three business types also have high demand in the early evening hours. Interestingly, six customers,

[74] These results match those of a recent survey conducted by the New England ISO (2003).
[75] Another way of looking at customer load profiles is to compute their load factor from the billing data available. We did this for the survey respondents, using 2002 yearly peak demand and total yearly volumetric usage, and found that 87% of the 53 survey respondents had load factors less than 70%. Of those with load factors higher than 70%, about two-thirds were industrial customers.
[76] Note that while 48 customers answered this question, five customers indicated more than one period as highest usage (morning and afternoon), and so appear more than once in the graph.

almost all industrial loads, report that their peak usage occurs at night (10pm to 8am). This may be a response to the TOU rate structure in effect for SC-3A customers from 1982 to 1998.

Figure 4-5. Temperature Sensitivity by Business Type

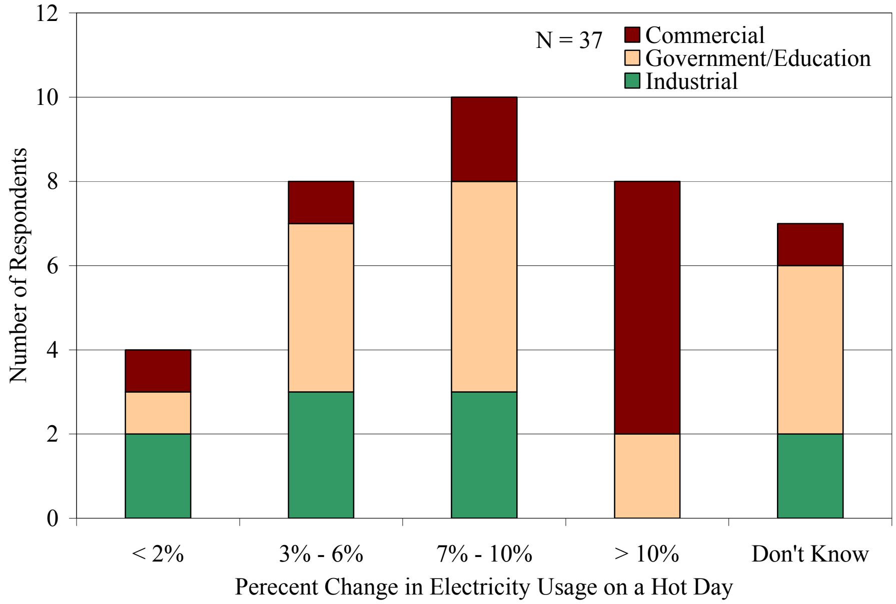
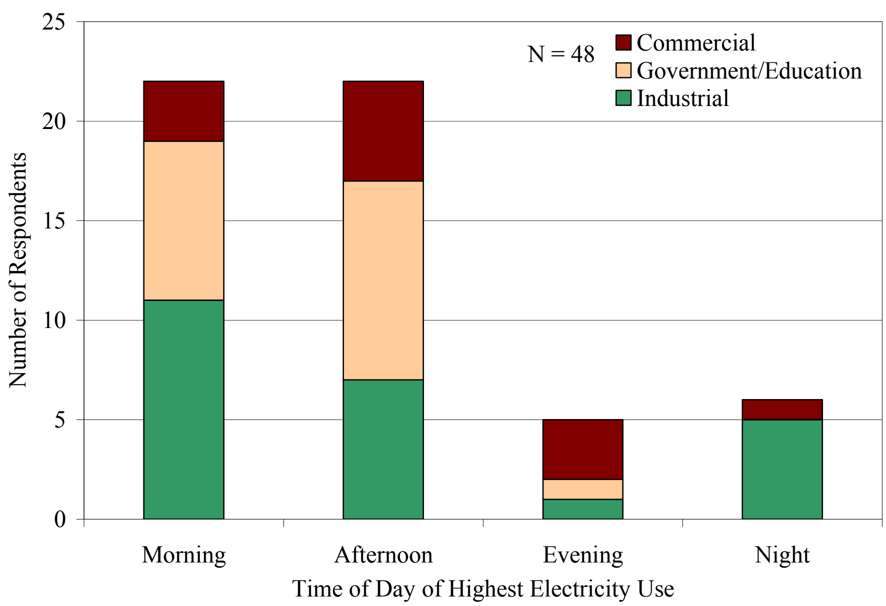


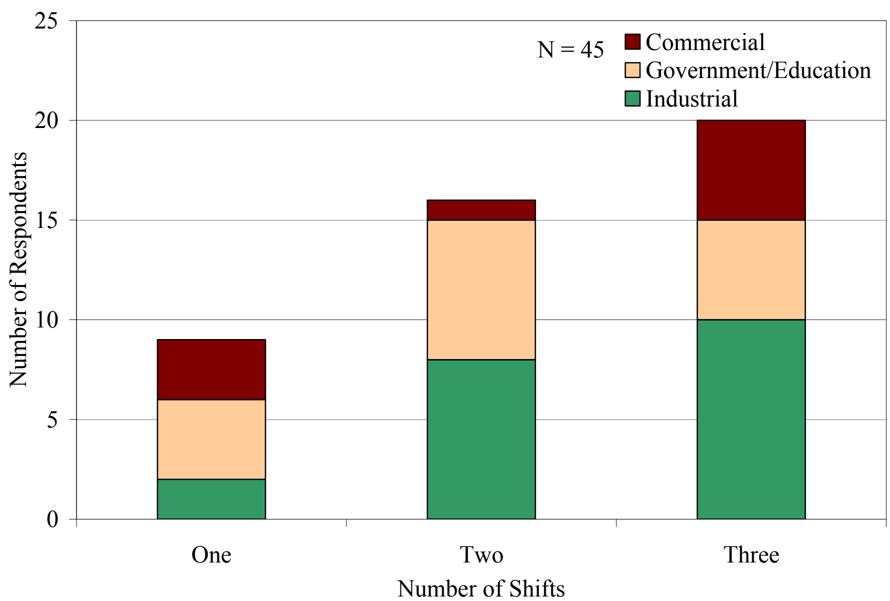
Figure 4-6. Time of Day of Highest Electricity Use



We also asked about seasonal trends in electricity usage. About 54% of respondents reported higher usage in one or more of the summer months (June through September), and 35% of respondents have higher usage during the winter months (December through March). Almost one third of respondents (31%) indicated no seasonality to their electric usage whatsoever. Of these, only half are industrial customers, whom we expect would be most likely to have limited seasonality to their loads.

The number of daily work or production shifts operated by respondents' facilities is summarized in **Figure 4-7**. Somewhat contrary to expectations, there are as many non-industrial customers with two or three shifts as industrial customers, although there are proportionally more industrial facilities with multiple shifts (90% vs. 67% for commercial customers and 75% for government/education). Few industrial facilities operate just one shift. Not surprisingly, we observe a relationship between the number of production shifts and load profile. One- and two-shift facilities tend to indicate morning or afternoon peak usage, while virtually all facilities with evening or night peaks operate three shifts. Not all three-shift facilities do so, however – afternoon is the most common peak period for these facilities.[77]

Figure 4-7. Number of Daily Work Shifts by Business Type



Finally, we asked customers whether their operations included batch production processes. Such customers may have more opportunities to re-schedule their production processes and shift the associated loads away from high-priced periods. Not surprisingly, virtually all of the non-industrial customers answered "no" for this question. In contrast, about 50% of the 19 industrial customers that responded indicated that their operations do include batch processes.

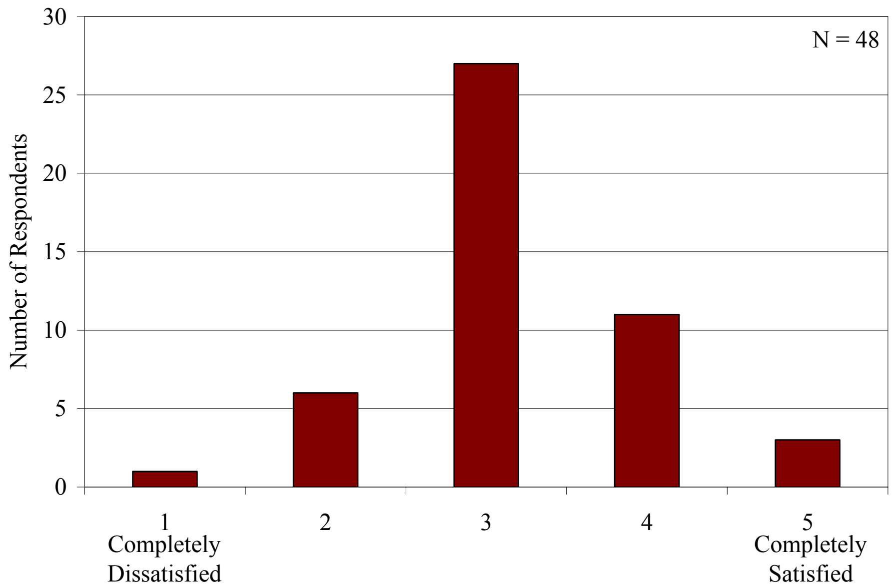
[77] Examining production shifts and computed load factors, we find that the majority of customers with load factors greater than 70% have three-shift operations.

4.2 How Have Customers Responded to RTP as the Default Service Tariff?

4.2.1 Customer Satisfaction with the SC-3A Tariff

We asked two questions about customers' satisfaction with the SC-3A tariff as it was redesigned in 1998. In the first, we asked them simply to rate their satisfaction on a scale of 1 to 5, with 1 meaning "completely dissatisfied" and 5 "completely satisfied". Customers appear moderately satisfied with the redesigned tariff – the average response is 3.19 for the 48 customers that responded (see **Figure 4-8** for the distribution of responses).

Figure 4-8. Customer Satisfaction with the 1998 Redesign of the SC-3A Tariff



We also asked customers to indicate which aspect of the redesigned SC-3A tariff could have been improved. We provided them with a list of potential responses, including options to specify an attribute not on the list or to indicate that no aspects displeased them, and asked that they select only one answer to this question. **Table 4-2** displays the options offered in this question along with customers' responses.

No one issue stands out among survey respondents as a major area of improvement. The most commonly cited issue was lack of information (16%), not an attribute of the tariff per se, but a criticism of the process. About a third of the respondents indicated that they had no major issues with the SC-3A tariff design at all.

These results suggest that customers are satisfied with the tariff itself. Our in-depth interviews shed some light on the reasons for this response – customers tended to express greater disappointment with the lack of development of the retail market than with the tariff design. Thus, while customers may not be completely satisfied with the choices available to them, they do not appear to explicitly identify major problems or issues with the SC-3A tariff or blame NMPC for shortcomings in the retail market.

Table 4-2. Primary Issue with 1998 SC-3A Rate Redesign

Issue	Percent of Responses (N=51)
Fixed-rate option should not have been a "take-or-pay" contract	14%
Fixed-rate option should have allowed for a proportion of demand to be nominated, not a fixed MW value	6%
More information should have been provided up front to assist my firm in making a better, more informed decision	16%
TOU-style demand charge should be removed	10%
The variable rate option (Option 1) should have covered only changes in electricity usage relative to a baseline level of load	14%
Other (please explain)	6%
None	35%

4.2.2 Preparation and Information Availability

In the survey, we asked six questions about customers' preparedness and information availability *prior to the 1998 transition.* We hypothesized that customers' perception of the amount of information received on retail service choices and forecasted prices, as well as their own level of experience, would influence the supply and hedging choices they made and their willingness to make these choices. Each question asked for a rating on a scale of 1 to 5, with 1 being the lowest (no information, totally unprepared, etc.), and 5 being the highest (complete information, fully prepared, etc.). The questions and responses are summarized in **Table 4-3**.

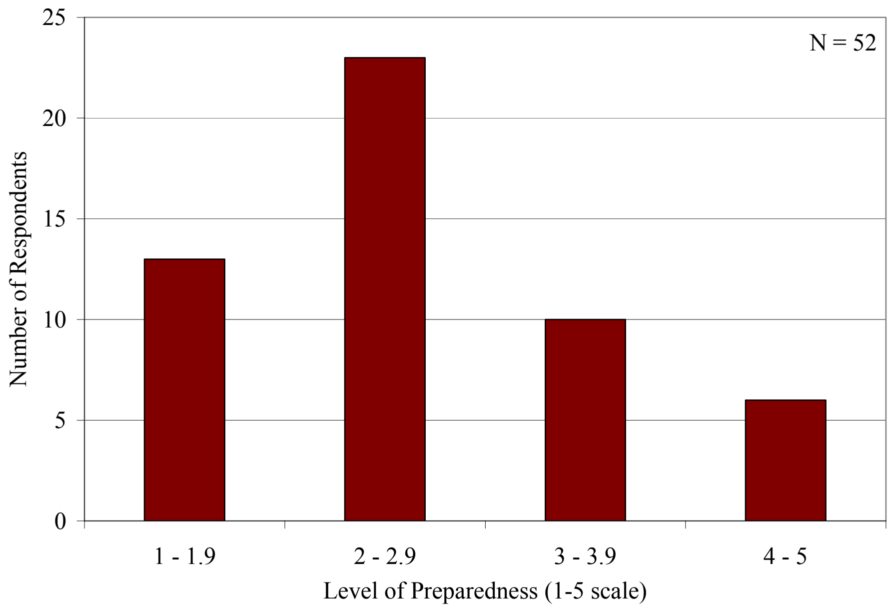
Table 4-3. Information Availability and Customer Preparation for Retail Competition in 1998

Question	Number of Responses	Average Response (1-5)
Preparedness to make the choice to nominate load for Option 2	51	2.73
Information on forecasted energy prices for the period 1998-2003	52	3.02
Familiarity with commodity hedging methods and products	52	2.42
Information on opportunities for procuring hedging arrangements from an entity other than Niagara Mohawk	52	2.48
Experience shopping for alternative electric commodity suppliers	51	2.02
Information on opportunities for procuring electric commodity from alternative suppliers	51	2.78

These results suggest that overall customers felt they had inadequate information, with the exception of information on price forecasts. Customers rated themselves as having particularly little experience shopping for competitive suppliers of electric commodity (average value of only 2.02).

We also computed a "preparedness" metric by averaging each customer's numeric responses across all six questions. **Figure 4-9** shows the distribution of results. Approximately 69% of respondents rated themselves relatively unprepared, as defined by an average response less than three. These results suggest that customers would have regarded additional information and/or training on issues and opportunities associated with opening retail electric markets to competition (e.g., hedging methods and products, procuring power from non-utility providers, market price forecasts) as helpful.

Figure 4-9. Customer Preparedness in 1998 for the Transition to Retail Competition



4.2.3 Price Response Capability

A major focus of this study is to evaluate the price response of SC-3A customers so as to better understand the demand response potential of RTP. We asked questions in the customer survey and in-depth interviews that get at customers' perceived willingness and capability to respond to varying and high prices. Through these questions, we explore factors that constrain customers' ability to respond, customers' assessment of their demand flexibility, and linkages between prior and recent investments in load management technologies and the ability of loads to be price responsive.[78]

[78] In Chapter 6, we estimate price response empirically using econometric models that incorporate customer billing data and various conditioning variables related to customer characteristics.

We first asked customers to characterize in general terms their current curtailment capability – whether they can shift load from one time period to another, forego electricity usage in certain periods (without making it up at another time), do both, or are unable to curtail at all. Over half (54%) of the 52 respondents claim that they are unable to curtail load (see **Figure 4-10**).[79] Of the 24 customers that responded positively, about two-thirds indicate that they are only able to respond by foregoing electricity usage, rather than shifting usage to other times. Some industrial customers report that they can utilize both strategies. Overall, institutional customer respondents were far more likely to indicate some type of response capability compared to other business types (62% versus 40% for industrials and 30% for commercial customers).

Price Response: Why Not?

In the customer survey, 54% of the customers indicated that they could not curtail or shift load in response to high prices. We probed this issue in our in-depth interviews in an attempt to identify and explore barriers to demand responsiveness, as stated by customers, and grouped their responses into four general categories.

Schedules are not adjustable:

- Our industrial processes cannot be adjusted on short order, either because of the nature of the processes or supply-chain considerations (e.g., industrial customers that utilize time-sensitive inputs or tightly scheduled delivery promises with little storage capability).
- Providing reliable and consistent service to our customers is our utmost priority (e.g., utilities, landlords, and some commercial institutions).
- We cannot adjust labor inputs without paying a penalty (e.g., union shops).

Savings would be insufficient:

- The adjustable portion of our load, and/or the importance of the commodity portion of our electric bill relative to total electricity costs, is too low to make the benefit worth the costs.
- Worker complaints render regular exercise of curtailments of lighting, cooling, etc. loads unattractive.

No time, no interest, skepticism, and frustration:

- We don't have staff available to attend to monitoring prices or to managing daily load when prices would dictate that we do so.
- We want to focus on our core business, not on energy management.
- Even if we figured out a way to reduce costs, a new charge or other change would erase these savings. We don't trust this situation.
- We're frustrated by regulations that prevent us from making technically superior business decisions, such as using cogeneration or combining across accounts.

Interest, but insufficiently prepared:

- We would like to be responsive, but we have not figured out how.

In a related question, we also asked survey respondents about specific actions undertaken at their facilities to reduce electricity usage in response to high prices over the past five years. We provided customers with a list of 11 potential responses, and also allowed them to specify actions not on the list, or no action at all.

[79] However, many of these customers were participants in NYISO DR programs (see section 4.3.6).

Figure 4-10. Customers' Appraisal of their Current Curtailment Capability

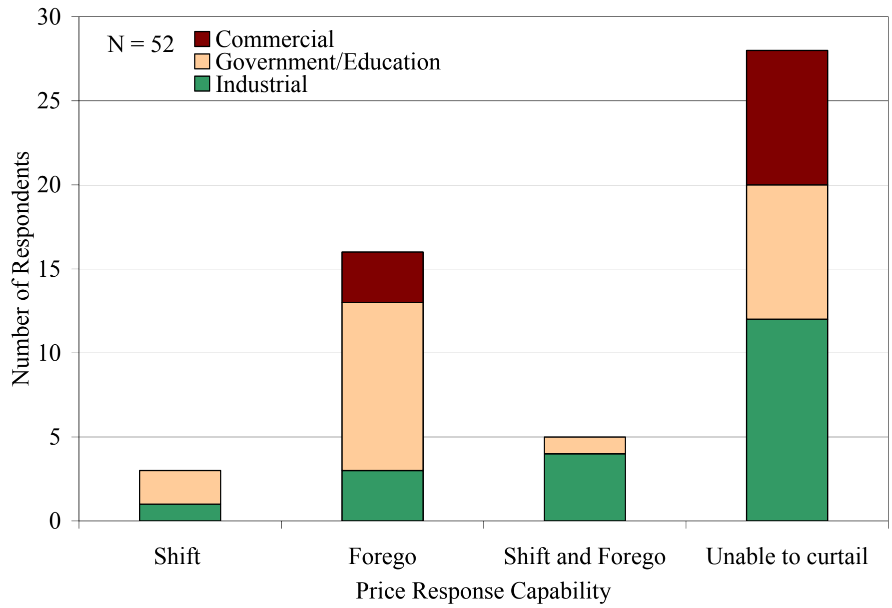


Table 4-4 summarizes the actions taken by the 24 customers who indicated they had some sort of response capability, and indicates which response capabilities and customer types are associated with each strategy. We find that the most common strategy (N=17) is relatively "low tech" – asking building occupants to voluntarily reduce usage. Other common strategies (cited by more than 10 customers) include reducing air conditioning or lighting energy use.

Table 4-4. Actions Taken in Response to High Electricity Prices

Actions Taken by 24 Customers with Response Capability	N	Response Capability			Business Type		
		Shift	Forego	Both	Ind.	Com.	Gov/ Edu.
None	3		●		○	○	○
Started onsite/backup generation	1		○				○
Asked employees to reduce usage	17	●	●	●	●	○	●
Turned off or dimmed lights	10		●	●	●	○	●
Reduced/halted air conditioning	15	○	●	○	○	○	●
Reduced/halted refrigeration/water heating	2		○				○
Reduced plug loads (e.g., office equipment)	3	○	○				●
Shut down plants or buildings	3		○	○	○		○
Halted major production processes	2		○	○	○		
Altered major production processes	4	○	○	○	○		○
Shut down equipment	12	○	●	●	●	○	●
Other	7		●	●	○		●

○ action indicated by one or two respondents
● action indicated by three or more respondents

These responses are consistent with the indication that these customers forego usage rather than shift to different time periods or days. Not surprisingly, industrial customers indicated halting or altering major production processes or shutting down equipment. Only one customer reported using onsite or backup generation to respond to high prices. Overall, government/education and industrial customers generally reported a greater number of actions per facility than commercial customers.

Price Response for the Customers That Said They Did: How and Why?

In response to probing questions about their ability and/or willingness to curtail or shift load in response to high prices, about 20% of the interviewees indicated that they are price-responsive and described their decision-making criteria and/or approach. Of these, two facilities were educational institutions and three were industrial customers.

The facility managers at the educational institutions indicated that they had flexibility to control/manage usage, particularly during holiday and summer breaks or slow periods because many buildings were nearly unoccupied and were thus easy targets for shedding load through centrally coordinated measures. The willingness to experiment and try new approaches to managing energy use (a perspective consistent with the academic "culture" of their educational institution) combined with support from budget-conscious senior management also was evident in the thinking of these energy managers.

One of the industrial customers had a batch process type operation. This customer indicated that they were sensitive to prices over a 24 hour period (rather than just 1-2 hours) and that they would curtail and/or shift usage for a sustained period of time (several hours to days) if prices went over their price threshold. Another industrial customer reported adjusting office loads in response to RTP. They indicated that they also curtailed process loads in response to an ISO DR system event (e.g., EDRP), but that they were not interested in doing so in response to RTP, given the nature of their product and the fact that any curtailment resulted in foregone production. The third industrial customer was quite large, consciously operated their facility with hourly electricity prices as a very important consideration in their scheduling and operations, and indicated that often had some "storage" inventory capability for their product. This customer had significant flexibility as to the timing of production and could shift load to off-peak hours but noted that if demand for their product was high or they had a tight delivery deadline to meet, they would not reduce electricity consumption no matter what the price.

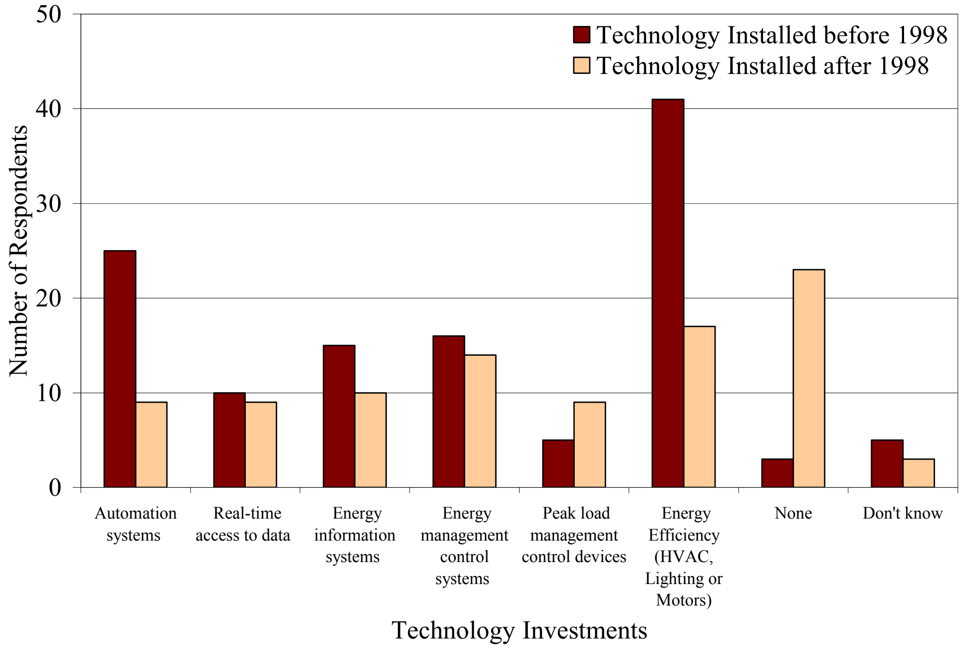
Customers were also asked if they had invested in load-management and energy-efficiency technologies at their facilities prior to and since the introduction of default RTP in 1998 (see **Figure 4-11)**. About 85% of respondents reported making investments prior to 1998. Energy-efficiency measures dominated these earlier investments; 95% of customers that made investments included energy efficient lighting, HVAC or motors in their upgrades, while 73% included monitoring or control measures. This reflects the emphasis of New York utility demand-side management (DSM) programs on promoting energy efficiency technologies in the early 1990s.

Only 45% of respondents reported making technology investments since 1998. All of them included energy management control systems (EMCS), peak load management controls or energy information systems in their investments – technologies targeted at demand response rather than energy efficiency.[80] Nonetheless, energy efficiency still

[80] Such technologies, if used to full advantage, can help customers develop automated demand response strategies, reduce transaction costs to implement load curtailments, and minimize service or amenity losses.

played a prominent role in these more recent investments; such measures were adopted by 74% of these customers.

Figure 4-11. Investments in Demand-Side Management Technologies



The observed shift in emphasis toward DR-enabling technologies may be attributed to several influences: (1) NYISO DR program marketing, (2) customer-initiated strategies to respond to RTP, or (3) New York State Energy Research and Development Agency (NYSERDA) programs that offer incentives for DR-enabling technologies. The NYSERDA programs are intended to enhance demand response state-wide through the adoption of advanced meters, EMCS, peak load management devices and energy-efficiency measures targeted at permanent load reductions. SC-3A customers may have received rebates for purchasing such equipment, or may have received the equipment through a load aggregator. Because these programs were not explicitly targeted to RTP, simply owning the equipment does not necessarily confer that customers actually use it to respond to RTP prices, although it improves the potential for response. Indeed, customer interviews suggest that many SC-3A customers are not fully aware of the potential applications and demand reduction potential of DR enabling technologies.

Nonetheless, it appears that customers' assessment of their demand response capability is well correlated with investments in enabling technology made since 1998. For example, 78% of respondents who indicated an ability to curtail load also made investments in DR enabling technologies such as automation systems, energy management control systems, and peak load management control devices since 1998. In contrast, only 25% of the respondents that had not made technology investments since 1998 indicated they could curtail. It appears that the deployment of DR-enabling technologies is an important driver that facilitates customers' perception of their curtailment capability. [81]

Energy Efficiency as a Hedge?

As part of the in-depth interviews, we explored customers' reasons for and the decision-making process behind their investments in energy efficiency and load management equipment and systems made since 1998. About 50% of these customers indicated that they had made significant investments in energy efficient lighting, HVAC systems, or motors and about a third reported that they were working with NYSERDA on projects that leveraged public benefit funds. In response to probing questions about whether their energy efficiency investments were linked to real-time prices, most customers indicated that they were not. One respondent commented, "we have been quite successful in reducing overall load working with the State, but not to respond to real time prices." Two customers, who recently reverted to default RTP service after extended periods on fixed rates, indicated that the combination of RTP and concerns about future electricity prices motivated them to look for ways to adjust load shape or reduce overall load. These customers described reviewing various plant practices in detail and found ways to reduce load through changes in system operations (e.g. pump operations) and energy efficiency investments in variable speed drives.

4.3 What Choices Have Customers Made?

A number of important policy questions arise when considering RTP as the default service option in a market environment with retail competition:

- To what extent does offering RTP as the default service tariff encourage customers to switch to competitive suppliers?
- To what extent do customers take steps to hedge themselves against price and volume risk?
- Do customers fully insulate themselves from price volatility by hedging all of their usage or do they hedge some portion of their load, leaving themselves exposed to dynamic prices on the margin?
- What types of hedging strategies (e.g., supply contracts, financial hedges) are employed by which types of customers?
- To what extent will customers who have made varying supply and hedging choices participate in DR programs in which they agree to curtail load when called or scheduled by an ISO?

In this section we address these questions by examining results from our customer survey, in-depth interviews, and information from NMPC's customer billing system. Specifically, we examine choices that customers made with respect to: (1) Option 2 nominations, (2) migration to competitive suppliers, (3) types of competitive supply contracts, (4) financial hedging arrangements, (5) propensity to fully hedge, and (6) participation in NYISO DR programs.

[81] However, as discussed in Chapter 6, DR-enabling technology adoption does not improve empirical estimates of price response.

In analyzing these choices, we employed the framework outlined in Figure 2-1 (see section 2.4), which identifies a variety of factors that we hypothesized could serve as drivers for the choices under examination. We present results from those factors that exhibited the strongest correlations or provided the most interesting stories.

4.3.1 Option 2 Nominations

The first choice that SC-3A customers faced during the transition to retail access was whether or not to nominate some or all of their load under NMPC's flat rate offering, Option 2. They had to make this choice in 1998 just prior to the opening of the competitive retail market. As described in Chapter 3, the Option 2 contract was relatively inflexible; it entailed take-or-pay provisions on power that was nominated in 100% load factor blocks separately for on-peak and off-peak periods, for up to five years. Customers could specify whatever amount of power they wished in each month, subject to these constraints. Because wholesale and retail power markets had not yet been established, customers had to rely on market price projections available at the time and their own judgment of what competitive retail suppliers might offer in the future to make this decision. They also had to predict how much electricity they would use in future years. As discussed earlier (see section 4.2.2), the majority of survey respondents said they did not feel they had adequate information to make this decision.

Based on information from NMPC's customer billing database, 24 customers, or 18% of the target population, chose to make Option 2 nominations. This result is not surprising given the market uncertainties, the take-or-pay, fixed price terms of the Option 2 contract and the fact that customers had to "opt-in" for Option 2. NMPC provided usage data for 23 of these 24 customers, which allows us to examine how their Option 2 nominations compared to their actual usage for the period between February 2000 and August 2003.[82] This approach allows us to address, with the benefit of hindsight, the actual outcome of customers' decisions to nominate load on Option 2.[83]

We are particularly interested in exploring two issues for this group of customers:

- To what extent did they insulate themselves from price volatility by hedging some or all of their usage on the Option 2 contract?
- How successful were they in forecasting their on-peak electricity requirements over a multi-year period? Did they avoid paying for electricity that they did not use?

To illustrate how we analyzed these issues, consider **Figure 4-12**, in which a hypothetical customer's Option 2 nominations are contrasted against actual usage on a particular day. The area under the "Actual Load" curve is the total daily energy usage (in kWh) used by the customer. The area under the dashed line is the energy usage committed under the Option 2 contract. In this case, the customer nominated 1 MW in the off-peak period, and 1.5 MW during peak hours.

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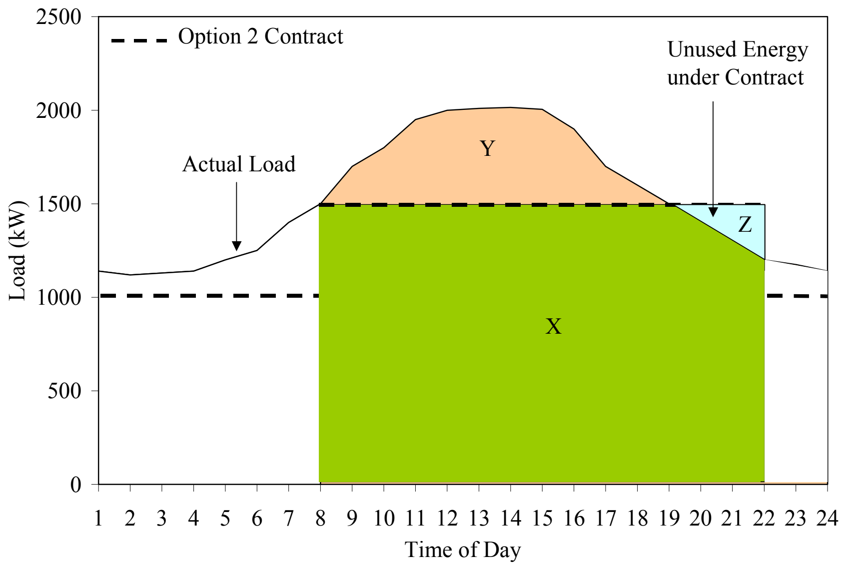
[82] Note that some Option 2 customers did not nominate load for the entire period.

[83] However, we cannot infer that these outcomes were exactly as intended by customers at the time the decision was made.

For this analysis, we examine peak usage only, as this is when we expect to see the greatest price variation. The customer's actual usage is divided into two portions: that which is covered by the Option 2 contract (area X in Figure 4-12), and excess usage not covered by the Option 2 contract (Y). A third area (Z) indicates load that was nominated and must be paid for under the take-or-pay provisions of the Option 2 contract, but that the customer did not use.

Figure 4-12. Option 2 Nominations and Actual Usage for a Hypothetical Customer



We defined two metrics to analyze the issues introduced above.

1. Percent of on-peak usage in excess of Option 2 on-peak nomination:

   $= Y / (X + Y)$

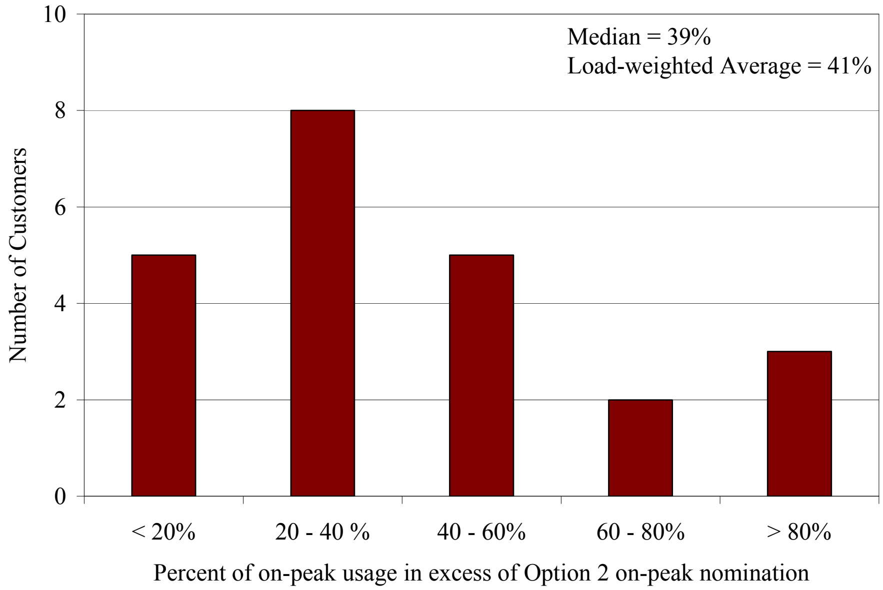
This measure quantifies the proportion of the customer's actual usage that was not covered by Option 2 nominations during the on-peak period.[84] This excess usage could either be priced at the hourly day-ahead market price under Option 1 or customers could contract with competitive suppliers on terms that they negotiated.

Figure 4-13 shows the distribution of customers according to this metric – the proportion of their on-peak usage in excess of their Option 2 nominations. The median value for the 16 customers analyzed is 39% and the load-weighted mean value is 41%. These results suggest that most of these 23 customers did not try to fully hedge price risk. Instead, they hedged about 60% of their on-peak usage at the Option 2 fixed price, with about 40% of

[84] We also compared customer's actual usage during off-peak periods to their off-peak nominations. Of the 24 customers, 6 customers did not nominate any load during the off-peak period, and thus faced day-ahead market prices during this period (or may have contracted with a competitive supplier for a flat-rate product), while 18 customers made nominations during the off-peak period.

the on-peak usage either priced at the day-ahead market price (Option 1) or covered by an alternative supply contract.

Figure 4-13. On-Peak Usage Relative to Option 2 Nominations



2. Percent of nominated on-peak load actually used during the on-peak period:

$$= X / (X + Z)$$

This measure quantifies the amount of Option 2-nominated on-peak electricity that was unused but had to be paid for under the terms of the contract. If a customer used all of its Option 2 nominated load (if the actual load line were at or above the nomination line for all on-peak hours) then the value of this metric would be 100%.

In aggregate, the 23 customers' actual usage was about 94% of their total nominated on-peak load over the time period examined. Only three customers' actual usage was significantly less than their on-peak nominations (one customer used only 27% while the other two used 58% and 80%), and actual usage for 14 of the customers was 100% of their nominated load or greater. Thus, very few customers were penalized financially because of the take-or-pay provisions of the Option 2 contract, despite the economic slowdown of the last few years. Customers appear to have addressed this risk by being conservative in committing to their forecasted on-peak power needs.

4.3.2 Supplier Choice

The second major choice that SC-3A customers faced was whether or not to switch to a competitive supplier. When the retail market in New York opened in 1998, all major parties involved in the restructuring settlement agreements expected that retail suppliers would enter the market and offer large customers a broad array of products and services that would be attractive alternatives to RTP. After five years, evidence from our study suggests that the market for retail electric supply in New York has been somewhat disappointing, both in terms of the number and types of active suppliers (termed ESCos in New York) and the limited range of products offered.

In the next two sections, we explore two aspects of customers' competitive supply choices: whether or not they switched to a competitive supplier and, for those that switched, what types of contractual arrangements were made (e.g., fixed rate contracts, contracts that indexed prices to wholesale markets).

Retail Choice: The Market and its Evolution from the Perspective of Customers

As part of our in-depth interviews with customers, we explored their decision-making process and experiences with retail suppliers since 1998, focusing on their preferred types of supply arrangements, the choices that they have been offered and their overall assessment and satisfaction with the competitive retail market. Based on responses, we grouped the comments from the 29 interviewees into six general categories: (1) satisfied with retail market experience and suppliers (or utility tariff that they selected), (2) ESCos have not actively marketed them or are not interested in serving their load, (3) dissatisfied with the types and pricing of supply offers, (4) haven't really shopped for a competitive supplier and have stayed with NMPC, (5) institutional barriers to accessing retail market, and (6) don't now or commodity supply decisions made elsewhere (e.g. headquarters).

In some cases, we assigned customers' responses to more than one category, typically in situations where there was a significant change in their experiences with suppliers (e.g., satisfied with contracts in first several years, but recent offers were not attractive) or because they expressed frustration with both the type and pricing of offers as well as the overall state and competitiveness of the retail market (e.g. few suppliers, not being marketed, few or no offers).

Customer Assessment of Experiences with Retail Market and Suppliers

Category	Number of Responses
(1) Satisfied with retail market experience (or utility tariff)	13 (+4)
(2) Dissatisfied – few or no supply offers from ESCos	6
(3) Dissatisfied – type and pricing of supply offers	9
(4) Not active - haven't shopped or just stayed with NMPC	2
(5) Institutional barriers within their organization to accessing retail market	2
(6) Don't know or decision made elsewhere	2

Customers in category (1) are primarily large industrial customers with flat loads or institutional sector customers that have successfully aggregated their loads. Overall, these customers seemed happy with their deals and in some cases had moved easily from one supplier or hedge product to another. In addition to the 13 customers that were relatively satisfied with their retail market experience, another four customers indicated that they were satisfied with their supply choice of remaining on default RTP tariff (Option 1) or selecting Option 2.

Six customers expressed dissatisfaction with the competitiveness or robustness of the retail market. Several interviewees said that no supplier was interested in serving their load, attributing this lack of interest either to their relatively small load or the nature of their load shape. These customers tended to be smaller institutions, hospitality, or seasonal industrial loads. For example, one interviewee mentioned having posted their load data on the web but generated no supplier interest. A few interviewees said that soon after deregulation there was an abundance of competitive suppliers, a number of them making active offers. However, in recent years, few, if any, suppliers approached them. Several interviewees raised parallels between electricity market deregulation and "the breakup of AT&T." For a commodity as important as electricity, some said, one wants a company one can trust, noting that this trust is not easily or quickly built. Two other interviewees said that they had been with a competitive supplier, but their supplier dropped them.

Nine customers expressed dissatisfaction with the type of and/or pricing of supply contracts, particularly the price premiums proposed by ESCos for a fixed rate contract. Most of these customers wanted a supply contract that hedged their price and volume risk, but were unable to find attractively priced offers. One interviewee noted that suppliers had become skittish about offering long-term fixed rate contracts, and no longer offered low, enticing, rates like those that were available when the market opened. In general, the array of products available was not as diverse as some customers said they would have liked. Two commented that while they wanted a supplier who would offer them efficiency or load management services as well, they could find no convincing offers. A customer with a relatively small load commented that he had contacted about a dozen suppliers and had only received two "ridiculous" offers.

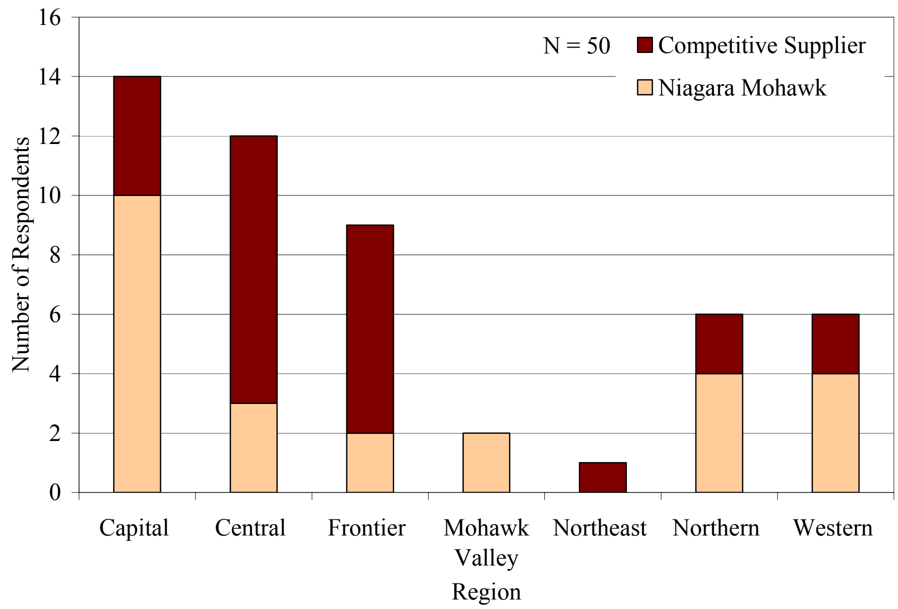
There were also a few customers who really hadn't tried to shop very much or who indicated that they were not that aware of the company's experience with ESCos because of their job position or because issues related to commodity procurement were made at a central headquarters. Finally, two institutional customers indicated that they had received interesting, potentially attractive offers from ESCos but that there were significant procurement and/or contracting barriers within their organization.

We first asked customers if they had taken service with a competitive supplier at any time since 1998. About 42% (of 52 survey respondents) said they had switched, 50% said they had stayed with NMPC, and 8% said they didn't know. We cross-referenced these answers against the customer billing system information provided by NMPC and found that a number of customers had switched to an ESCo but did not answer the survey accordingly. This information reveals that 52% of survey respondents (out of 50 survey respondents for whom information was available) took service with an ESCo at some point since 1998, and 48% stayed exclusively with Niagara Mohawk. For the results that follow, we use this information, not the survey responses, in analyzing the characteristics of customers that switched to a competitive supplier versus those that stayed with NMPC default service.

4.3.2.1 Customer Characteristics and Supplier Choice

We find a significant relationship between customer geography and propensity to switch to competitive suppliers. Customers located in the Capital region were less likely to switch than those in other service areas (29% switched in the Capital zone vs. 61% in other zones) (see **Figure 4-14**). This result is significant at the 95% confidence level. As noted in Chapter 3, a transmission bottleneck between the Capital region and other NMPC load zones causes higher and more volatile Capital-zone prices when demand is high. The highest switching rates are found in the Central region, where 75% of customers have taken ESCo service compared to 45% in other regions. This result is significant at the 90% confidence level.

Figure 4-14. Supplier Choice by NMPC Load Zone



Survey respondents' competitive-supply switching rates are presented by various customer characteristics in **Table 4-5**. Of the three business types, commercial customers were most likely to switch to a competitive supplier for electric commodity service. Industrial survey respondents were, surprisingly, less likely to leave NMPC than non-industrial (commercial and government/educational) respondents – this result is statistically significant at a 99% level.

The relative contribution of electricity costs to overall operating costs doesn't seem to be a large driver for customer switching, although customers reporting electricity costs less than 3% of operating costs were somewhat more likely to switch. As discussed earlier, this may be more of an indication of the customers' perception of these costs than their actual size relative to the facility's total budget.

Customers with temperature-sensitive loads tend to take supply from ESCos with higher frequency. Seasonality, which is covariate with temperature sensitivity, is also correlated with the likelihood of customer switching. Customers that reported peak electricity usage during the summer were more likely to choose a competitive supplier than non summer-peaking customers (this result is significant at the 95% confidence level).

Finally, we find that participants in the NYISO's two emergency DR programs were less likely to switch than non-participants. This result is statistically significant at the 95% confidence level.

Table 4-5. Supplier Switching Rates by Customer Characteristics

Customer Characteristic		Number of Respondents	Percent Taking Competitive Supply*
Business Type	Industrial	19	26%
	Government/education	20	60%
	Commercial	11	82%
Electricity Expenditures as Percent of Operating Costs	Less than 3%	11	64%
	Between 3% and 10%	12	42%
	Greater than 10%	17	59%
	Don't know	8	50%
Percent Change in Electricity Usage on Hot Days	6% or less	11	27%
	Greater than 6%	17	71%
	Don't know	7	57%
Number of Operating Shifts	One	8	63%
	Two	15	53%
	Three	19	47%
Season of Highest Electricity Use	Summer (May – September)	20	70%
	Other seasons	30	40%
EDRP and/or ICAP Enrollment (2001 – 2003)	Enrolled at least once	22	32%
	Never enrolled	28	68%

*at any time since 1998

4.3.2.2 Customers' Revealed Preferences for ESCo vs. Utility Supply

Having examined correlations of various factors with customer propensity to switch to a competitive supplier, we now estimate a revealed preference model that employs these factors in a statistical framework with greater predictive power. The results of this estimated logistic model are summarized in **Table 4-6**. The overall performance of this model is very good; three variables are globally significant at least at the 95% level and one at the 90% level. The very low p-value (<0.0001) for the likelihood ratio test also suggests an excellent fit overall.[85]

The estimated model coefficients[86] (log-odds ratios) and related p-values are reported in the topmost table in Table 4-6. To facilitate interpretation of the results, we convert the log-odds ratios to odds ratios, or the relative likelihood of a customer switching to a competitive supplier, rather than staying with NMPC. If the odds ratio is greater than one, the probability of switching is greater than the probability of staying with the utility; if it is less than one, the customer is more likely to stay with the utility than switch. Key findings are as follows:

- Customers located in the Capital region, a region with high transmission congestion, are four times less likely to switch to a competitive supplier than stay with the incumbent utility. This result may seem counter-intuitive in that we might expect

[85] The very low p-value indicates that we must reject the null hypothesis that all model coefficients are equal to zero, meaning that at least one model coefficient is non-zero.
[86] These coefficients refer to the β' vector described in section 2.6.1.

customers to switch in regions with higher, more volatile prices as a strategy to lower their costs. However, such conditions also make it riskier for ESCos to provide firm service. This, plus evidence from customer interviews about the scarcity of retail market offerings, suggests that this result is probably driven more by what ESCos offer in various regions than customer preferences per se.

- Customers with peak electricity usage in the summer are 10.4 times more likely to switch to a competitive supplier than stay with utility commodity service. This suggests that customers with coincident loads are more inclined to seek opportunities to minimize their electricity costs than other customers.
- Industrial customers are almost 9 times more likely to remain on utility commodity service than switch to competitive suppliers.[87]
- Customers that have enrolled at least once in EDRP and/or ICAP/SCR are almost 4 times more likely to remain on utility commodity service than switch to a competitive supplier.[88] This may indicate complementarities between the factors that motivate customers to participate in these programs (e.g., good citizen factor, helping to avoid system emergencies) and a tendency to stay with the default utility service provider.

Table 4-6. Predicting Customer Switching – Results of Revealed Preference Model

Parameter	Estimate (Log Odds Ratio)	p-value	Odds Ratio Point Estimate
Intercept	1.02	0.07	
Summer Peaking	2.34	0.01	10.4
Located in Capital region	-1.38	0.12	0.25
Industrial customers	-2.22	0.01	0.11
Enrolled at least once in EDRP and/or ICAP/SCR over the last three years	-1.49	0.05	0.23

Overall Model Fit (Likelihood Ratio Test)	
Chi-Squared Statistic	24.04
p-value	<0.0001

4.3.3 Types of Competitive Supply Contracts

We are also interested in the types of supply arrangements that customers entered into with ESCos. In particular, an important policy question is the extent to which customers enter into supply contracts that hedge price risk. In the previous section, we treated customers as having switched if they did so *for any period* within the past five years.[89] However, the reality is that few arrangements have lasted the full five years; most competitive supply contracts have terms of one or two years. It is thus useful to obtain a

[87] This is simply the reciprocal of 0.11, the odds of choosing a competitive supplier over staying with NMPC.
[88] Again, this is the reciprocal of 0.23, the odds of choosing a competitive supplier over staying with NMPC.
[89] We take this approach again when we examine customers' propensity to fully hedge in section 4.3.5.

sense of the evolution in and popularity of various types of supply contracts between ESCos and customers since the retail market opened in 1998.

We asked survey respondents that chose a competitive supplier to provide information on the types of contractual arrangement they had held in each winter and summer period since November 1998. **Table 4-7** shows the evolution in commodity supply arrangements reported by these survey respondents (and those that we know remained on Option 1) over three illustrative time periods: winter 1998/99 (which corresponds to the opening of NYISO markets), summer 2001 (shortly after customers first saw day-ahead market prices spike to very high levels), and summer 2003 (the most recent period available).

Table 4-7. Types of Electric Commodity Supply Arrangements

Type of Supply Arrangement	Winter 1998/99	Summer 2001	Summer 2003
Flat Rate	7	3	4
TOU Rate	6	6	6
Volumetric Collar	2	3	1
Price Index	2	5	9
NMPC SC-3A (Option 1)	27	27	24
Percent Hedged	*34%*	*27%*	*25%*
Number of customers reporting	*44*	*44*	*44*

Glossary of terms:
FLAT RATE: a single rate applied to all metered kWh usage.
TIME-OF-USE RATE: a fixed schedule that divides certain seasons and hours of the day into peak and off-peak periods with pre-specified rates applied to metered usage in each period.
VOLUMETRIC COLLAR: a rate that is fixed for a specified range around a specified volume of electricity usage. If consumption is above or below the specified range, the excess or shortfall is typically settled in the real -time market.
PRICE INDEX: a rate paid for metered usage that is derived from another price series (usually SC-3A Option 1 prices in this context)
NMPC SC-3A (OPTION 1): the default RTP tariff offered by NMPC for commodity service

The first three supply arrangements in Table 4-7 constitute fully hedged contracts – they completely hedge a customer against both price and volume risk (see *Taxonomy of Supply and Financial Hedging Products* below). It is clear that the proportion of these hedged commodity supply arrangements is declining – in 1999, 34% of the respondents held hedged supply contracts versus 25% by 2003. On the other hand, price indexes (in most cases indexed to SC-3A Option 1) appear to be increasing. In our follow-up interviews, many customers claimed that the only service offering now available is an index to SC-3A service with a small shopping credit. Initially, when the retail market opened, a number of ESCos offered flat or fixed-rate options that were attractively priced. Five years later, it appears that fewer ESCos offer such products, and those that still do have changed their pricing relative to products that are indexed to day-ahead market prices (i.e. increased risk premiums for fixed rate offers).

Taxonomy of Supply and Financial Hedging Products

Utilities, ESCos, or other third parties may offer various products that provide hedging options to electric customers. These products may include utility electric service rates, alternative commodity supply contracts and financial hedges that are separate from the physical delivery of power.

The following table summarizes the range of products and their risk profiles from a customer perspective. Commodity products that are indexed to wholesale electric market prices are highest risk, in terms of price volatility, as customers are exposed to market prices for their full load. Cap and swap type products provide partial hedging for price risk by limiting the portion of a customer's load that is exposed to market prices. Customers can also insulate themselves from *both* price and volume risk with various products, which include traditional utility fixed-rate and time-of-use rates.

We are interested in two types of hedging: (1) partial, cap and swap type hedges, which leaves customers exposed to market prices for their marginal usage above some pre-specified baseline, and (2) full price and volume risk hedges, which insulate customers completely from hourly price fluctuations and may dampen their incentive to respond to market prices.

Risk	Product Class	Product	Baseline or Part of Baseline	Incremental Usage
HIGH	*Index Type Products*	One-part RTP Purchasing through ISO	N/A N/A	Day-ahead prices Real-time prices
↑	*Cap Type Products (for price risk)*	Cap Collar DR Technology	Day-ahead prices (risk limited) Day-ahead prices (risk limited) Day-ahead prices (risk limited)	Day-ahead prices Day-ahead prices Day-ahead prices
↓	*Swap Type Products (for price risk)*	Two-part RTP Swap Long term supply contract Energy efficiency investments Take-or-pay contract for part of usage	Hedged Mostly hedged Hedged Hedged Hedged	Day-ahead prices Day-ahead prices Real-time prices Day-ahead prices Day-ahead prices
LOW	*Hedges Covering Price and Volume Risk*	Fixed rate contract Time-of-use type tariff Volumetric collar Take-or-pay contract for full usage	Hedged Hedged Hedged Hedged	Hedged Hedged Hedged Hedged

4.3.4 Financial Hedging Options

In addition to taking physical supply from an ESCo, SC-3A customers also had the opportunity to purchase financial hedging products from retailers. A major policy question centers on which entities should provide such products – regulated utilities, energy retailers, or financial services providers. In New York, the competitive retail market was relied upon to offer financial hedging products.

We asked survey respondents to indicate what types of financial hedges they had bought, if any, and in what time periods (again, asking about each winter and summer period since the market opened). The results are presented for the 32 customers that answered this question in **Table 4-8**, for the same three time periods examined for physical supply contracts. It appears that market activity for financial hedging products is modest – only a few customers have taken financial hedges at any time since 1998, though activity is increasing. The number of customers exposed to RTP (those not covered by a hedged physical supply option) taking financial hedges has almost doubled, from 16% in winter 1998/99 to 30% in summer 2003. This may be an indication that customers are increasingly searching for alternative hedging opportunities in response to the decline in flat-rate ESCo supply offerings and the sunset of NMPC's Option 2 offering.

Table 4-8. Types of Financial Hedging Products

Financial Hedge Product Type	Winter 1998/99	Summer 2001	Summer 2003
Price Collar	0	0	1
Price Cap	0	1	2
Financial Swaps	3	5	4
Number of customers reporting	*32*	*32*	*32*
Number of customers exposed to RTP (not taking hedged supply)	*19*	*21*	*23*
Percent of customers exposed to RTP that took a financial hedge	*16%*	*29%*	*30%*

Glossary of terms:
PRICE COLLAR: The rate paid is determined by a price series that varies, but can be no higher than a specified cap price or lower than a specified floor price.
PRICE CAP: The rate paid is determined by a price series that varies, but can be no higher than a specified cap price.
FINANCIAL SWAP: the price is fixed for a given load profile (typically a demand block or series of blocks). The settlement is financial using typically day-ahead prices. Also known as a *Contract for Differences*.

Survey respondents were asked whether they had various types of hedging products: price collars, price caps and financial swaps. Swaps appear to be slightly more common than caps or collars. Each of these product types constitute partial, price risk hedging. That is, customers with such products are still exposed to price risk on any marginal usage not covered by their hedge. This is an important feature of these products from the standpoint of demand response.

4.3.5 Customer Propensity to Hedge Price and Volume Risk

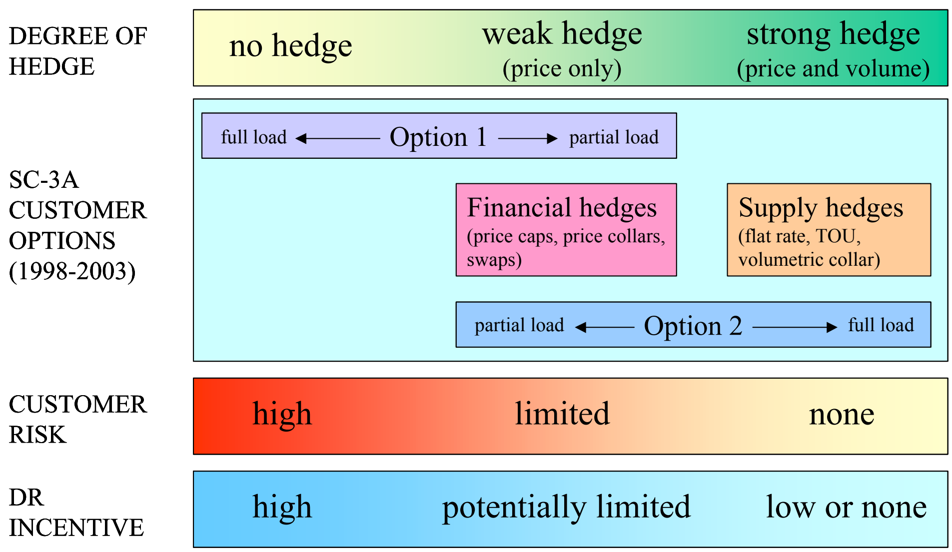
The previous sections have addressed trends in customer adoption of various types of hedging options. We examined physical supply hedging options – NMPC's Option 2 and competitive supply options – as well as financial hedging products. In this section, we classify customers according to the degree to which they have hedged themselves and attempt to characterize the customers that opted to hedge according to the factors outlined in Figure 2-1.

Three "degrees" of hedging may be assumed by customers on RTP (see **Figure 4-15**).[90] Customers may hedge both price and volume risk, fully insulating themselves against price volatility for all their electric consumption. We term this "strong" hedging and classify customers that took hedged supply options (flat rate, TOU and volumetric collars) to be "strongly hedged". Alternatively, customers may opt for a partial hedge that

[90] See *Taxonomy of Supply and Financial Hedging Products* earlier in this chapter for a discussion of the range of possible hedging products and their relative coverage of price and volume risk.

covers price risk for a bounded quantity of electricity, but that leaves them exposed to hourly-varying prices for any marginal usage in excess of that covered by the hedge – we term this "weak" hedging. The customers in our sample that chose financial hedging products (price caps, price collars or swaps) as well as four customers that nominated a portion of their usage on Option 2 fall into this category.[91] Finally, customers may choose not to hedge at all, remaining fully exposed to hourly-varying prices for all their electric commodity usage.

Figure 4-15. Hedging, Risk and DR Profiles of SC-3A Customers' Supply and Product Options



We hypothesize that the degree to which customers hedge impacts the level of price response that can be expected (see Figure 4-15). By our definition, strongly hedged customers do not see RTP prices for marginal usage, because their hedging arrangements cover their entire loads. Because the incentive to respond is effectively removed, we expect these customers to be less price-responsive.[92]

Weakly hedged customers, while protecting themselves from some of the volatility inherent in wholesale market-indexed prices, do see RTP signals on the margin (this is analogous to two-part RTP, which uses a CBL as a partial hedge). Economists argue that these marginal signals provide the same price-response incentives as would be seen by a fully un-hedged customer, because the same potential for savings exist from conservation during high-priced hours (see, for example, O'Sheasy, 1997; Borenstein, 2002). For our econometric analysis, we follow this theory and do not treat weakly hedged customers differently from those fully exposed to RTP. However, our interviews suggest that customers do not necessarily view RTP in terms of *incentives* – many are more accustomed to viewing it in terms of *risk exposure*. For these customers, subjecting their entire load to time-varying prices represents a much larger risk than would just marginal

[91] All four customers purchased at least 10% of their usage at variable prices.
[92] We attempted to construct a "strong-hedging" variable for use in our demand models (Chapter 6), but the variable did not contribute to explaining variations in customers' price response.

usage, which may lend these customers to pay greater attention to high prices. Thus, it is reasonable to consider that the actual level of price-responsiveness exhibited by weakly hedged customers may be lower than for those that are completely un-hedged. Further research is needed to determine if this is indeed the case.

Customer Choice: On RTP, but not Responsive

Why did some customers who reported having little interest in adjusting load in response to price choose to remain on RTP rates? We asked several questions in our interviews that explored customers' survey responses in more depth for those customers that chose to remain on RTP who also indicated that they were unable to curtail load and/or hadn't taken any actions to reduce electricity usage in response to high prices. A number of themes emerged in their responses.

- First, several customers indicated that in October 1998 when they had to choose initially among the NMPC tariff options and/or switching to an ESCo, it was unclear to them how the market would unfold. Moreover, at the time, they didn't have the time or resources to assess Option 2 or search out ESCo offers and so were placed by NMPC on the default RTP tariff. In effect, they chose not to choose.
- Second, other customers indicated that some or all of their load had been on Option 2 and/or an ESCo contract but these options had now expired, leaving them back on RTP default service tariff. Some of these customers stated that they didn't expect to remain on the default RTP service indefinitely. Instead, they saw it as a transitional phase while they sought superior options (RTP as "holding ground").
- Third, a few customers commented that SC-3A Option 1 prices are "just the price of electricity." These customers don't interpret time-varying rates as an implicit call to adjust their usage. Such customers said that they review their bill only at the end of the month and don't look at hourly prices.
- Fourth, a few institutional sector energy managers noted that it was risky and/or difficult to take supply options other than the default RTP service, since doing so would require substantial effort and time on their part in order to get elected bodies to approve competitive solicitations or awards.

All of these comments point to the possibility that the fact that RTP is the default service may explain why customers that are un-hedged also indicate that they are not capable of or interested in demand response.

4.3.5.1 Characteristics of Customers that Chose to Strongly Hedge

Policymakers are interested in knowing which types of customers are likely to adopt various levels of hedging. For the 44 survey respondents that provided sufficient information to be classified, we determined that 17 (39%) were strongly hedged at some time since 1998, according to our definition.[93] **Table 4-9** shows the distribution of strongly hedged customers (versus non-strongly hedged ones) according to several customer characteristics.

We find that more than half of government/education customers were strongly hedged, compared to less than a quarter of industrial customers.

[93] Our sample of weakly hedged customers was very small – thus we grouped them along with fully un-hedged customers into a "not strongly hedged" category.

Table 4-9. Strong Hedging Propensity by Customer Characteristics

Customer Characteristic		Number of respondents	Percent Taking a Strong Hedge*
Business Type	Industrial	18	22%
	Government/education	18	55%
	Commercial	8	38%
Season of Highest Electricity Use	Summer (May – September)	18	50%
	Other Seasons	26	31%
Electricity Expenditures as Percent of Operating Cost	Less than 3%	10	60%
	Between 3% and 10%	13	54%
	Greater than 10%	12	25%
	Don't Know	7	14%
Technology Investments Since 1998	Investments made	22	50%
	No Investment	22	27%
EDRP Enrollment (2001 – 2003)	Enrolled at least once	18	27%
	Never Enrolled	26	46%
ICAP/SCR Enrollment (2001 – 2003)	Enrolled at least once	6	0%
	Never Enrolled	38	45%

*at any time since 1998

Almost all of the strongly hedged customers (15 of 17) indicated that their peak electricity usage occurs in the daytime (morning, afternoon or both). Respondents that indicated summer-peaking loads were more likely to strongly hedge than customers with peak usage at other times of year.

All but one of the strongly hedged customers operates more than one production shift per day. Approximately half (47%) of the customers with more than one daily production shift were strongly hedged, versus only one out of seven single-shift customers.

Surprisingly, customers with lower electricity intensity were more likely to take a strong hedge than customers for whom electricity makes up a higher share of operating costs. Of the 17 strongly hedged respondents, 13 indicated electricity expenditures less than 10% of total operating costs.

Customers that installed DR-enabling technologies after 1998 are more inclined to strongly hedge than those that didn't. Finally, facilities that have participated in either EDRP or ICAP are less likely to fully hedge than those who did

4.3.5.2 Customers' Revealed Preferences for Strongly Hedging

We estimated a revealed preference model to explore in greater depth the factors that contribute to customers' propensity to strongly hedge. The results of the logistic model are summarized in **Table 4-10**. The overall performance of this model is good; all variables are globally significant at the 6% level. The low p-value (0.0041) for the likelihood ratio test also suggests a very good fit overall.

The estimated model coefficients[94] (log-odds ratios) are reported in the topmost table in Table 4-10. As before, we convert the log-odds ratios to odds ratios to interpret results – an odds ratio greater than one indicates that the probability of strongly hedging is greater than the probability of not strongly hedging. Key findings include:

- Government/education customers are six times more likely to strongly hedge than other customers. Our customer interviews reveal that in several cases this is due to several such customers pooling their loads to buy an aggregated, fully hedged electric commodity contract.
- Customers that indicated electricity expenditures less than 10% of their total operating costs are 10 times more likely to strongly hedge than those indicating higher electricity costs.[95]
- Customers that invested in DR-enabling technologies since 1998 are six times more likely to strongly hedge than those that didn't. While somewhat counterintuitive, this result may imply that customers who received equipment did so for reasons other than responding to RTP (e.g., to assist in responding to NYISO DR programs, or to identify inefficiencies in building operations).

Table 4-10. Predicting Strong Hedging – Results of Revealed Preference Model

Parameter	**Estimate (Log Odds Ratio)**	**p-value**	**Odds Ratio Point Estimate**
Intercept	-0.96	0.13	
Government/education customers	1.98	0.05	5.9
Electricity expenditures >10% of total operating costs	-1.95	0.06	0.1
Invested in DR technologies after 1998	1.79	0.06	6.0

Overall Model Fit (Likelihood Ratio Test)	
Chi-Squared Statistic	13.26
p-value	>0.0041

To conclude, we find that some of the factors that describe the SC-3A customers that chose to fully insulate themselves from price volatility are intuitive – they tend to be day-peaking, largely institutional sector customers with multiple shifts that face somewhat higher costs than other survey respondents. A number of customer-specific characteristics likely interact to influence how a customer makes the complex decision to invest in a fully hedged product. However, one must also consider the context in which these decisions were made. Our in-depth interviews shed some light on this question. The majority of customers indicated that they would prefer to be fully hedged but that competitive retailers were not offering fully hedged products or the offers received were

[94] These coefficients refer to the β' vector described in section 2.6.1.
[95] This is simply the reciprocal of 0.1, which indicates the chances of customers with higher than 10% electricity expenditures of choosing a strong hedge.

unattractive due to high risk premiums. Thus, to extend these results to other jurisdictions it is important to bear in mind that the observed rates of hedging in New York may be lower than would be the case in places with a wider, more attractive range of hedging product options.

4.3.6 NYISO DR Program Participation

During the last three years, NMPC SC-3A customers have had the option of participating in one or more of the NYISO DR programs. Statewide, participation in the two emergency programs, EDRP and ICAP/SCR, has been quite strong, while the economic program, DADRP, has seen limited enrollment (see section 3.7) and low bid activity. A similar trend is observed for NMPC SC-3A customers. Of the study population of 149 accounts, only one is enrolled in DADRP, while ICAP/SCR and EDRP have seen modest to fairly sizeable enrollment (see section 4.1.1). In this section, we explore the characteristics of survey respondents that participated in the emergency type programs, EDRP and ICAP.

Emergency DR Programs vs. RTP

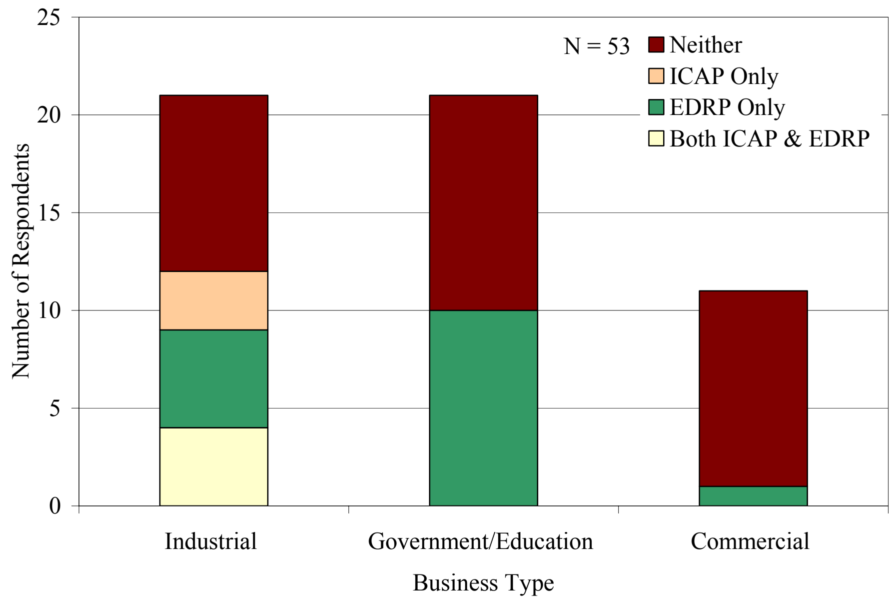
About 38% of survey respondents indicated that they were enrolled in the NYISO emergency DR programs – primarily EDRP but several enrolled in ICAP/SCR. As part of our in-depth interviews, we asked probing questions about participation in NYISO DR programs. A number of customers offered answers which provide insights into the issue of why firms that are willing to curtail load in response to declared EDRP events with two hours notice would not be willing to do so in response to day-ahead hourly pricing signals.

- "We'll respond when asked, otherwise we're not watching."
- "We respond because it benefits the community, as well as having some advantage to our financial bottom line."
- "EDRP payments make it worth our while, so we do it when we can, but RTP prices are not high enough."
- "We can adjust our load from time to time, based on special arrangements between management and facilities, or between one plant and another, or based on the goodwill of workers who understand the short-term need to conserve in order to prevent blackouts, but we're not interested in making a regular, profit-oriented, practice out of it."

These responses suggest that an additional share of the customer base is willing to curtail and/or shift load relatively infrequently in situations where they are reacting to an "emergency" situation that is defined by a grid operator or governmental entity and for which they are paid higher prices (e.g., \$500/MWh floor payments). They also suggest that the differential willingness to respond is not solely a function of the difference in RTP prices observed by customers during high price periods (e.g., \$150-250/MWh) and EDRP payment levels (\$500/MWh), but may also reflect "good citizen" motivations.

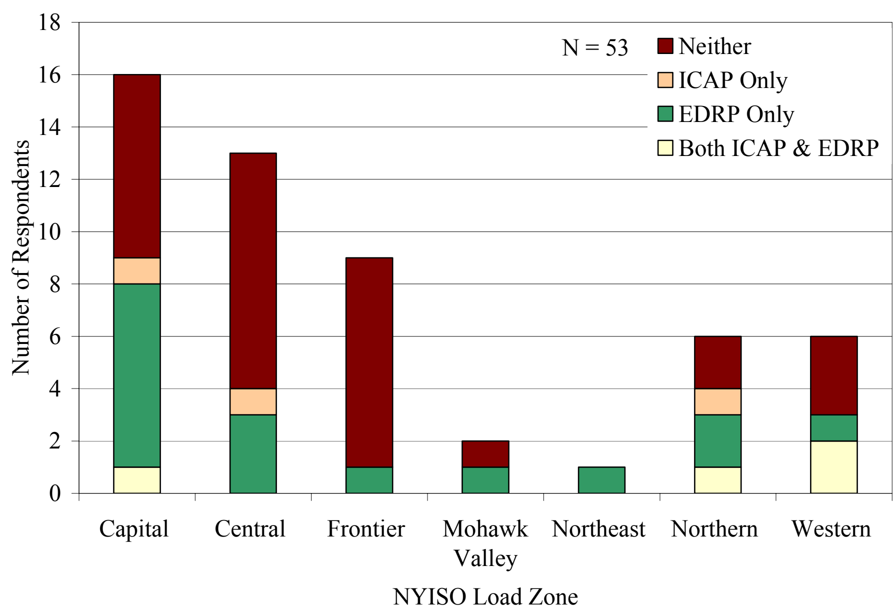
Figure 4-16 shows the participation of NMPC survey respondents in EDRP and ICAP by business type. We considered each customer a program participant if they enrolled for at least one year. Accounting for multiple program participation, slightly more than half (57%) of industrial customers in our sample participated in at least one emergency DR program (EDRP or ICAP/SCR). In contrast, government/education customers showed slightly less program participation (48%) and this exclusively in EDRP. Participation by commercial customers in any program is extremely low – only one customer in our sample was enrolled, in EDRP.

Figure 4-16. Participation of Survey Respondents in NYISO Emergency Programs



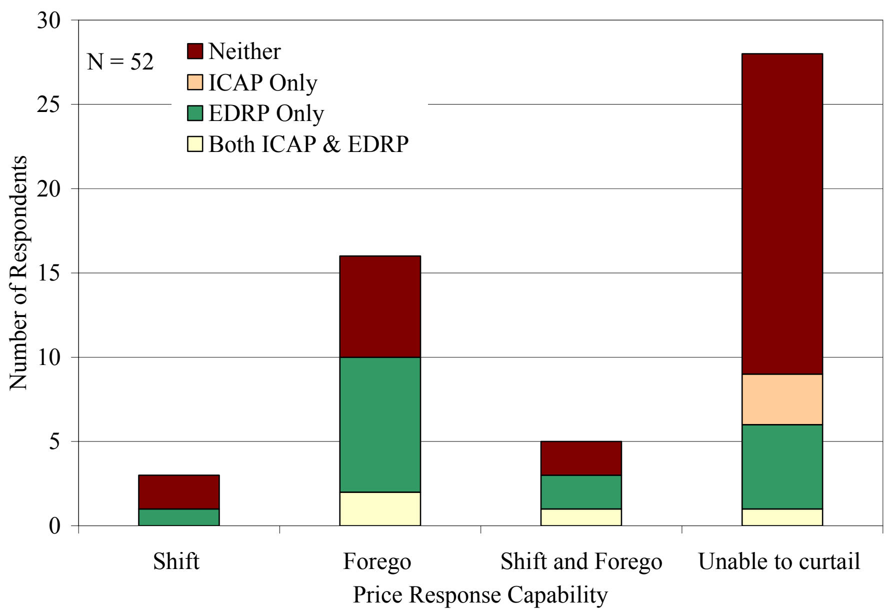
There are some regional differences in NYISO emergency program participation among survey respondents. Participation rates in the Central and Frontier regions have been lower than other NYISO pricing zones (23% versus 58%) (see **Figure 4-17**).

Figure 4-17. Regional Variations in NYISO Emergency Program Enrollment



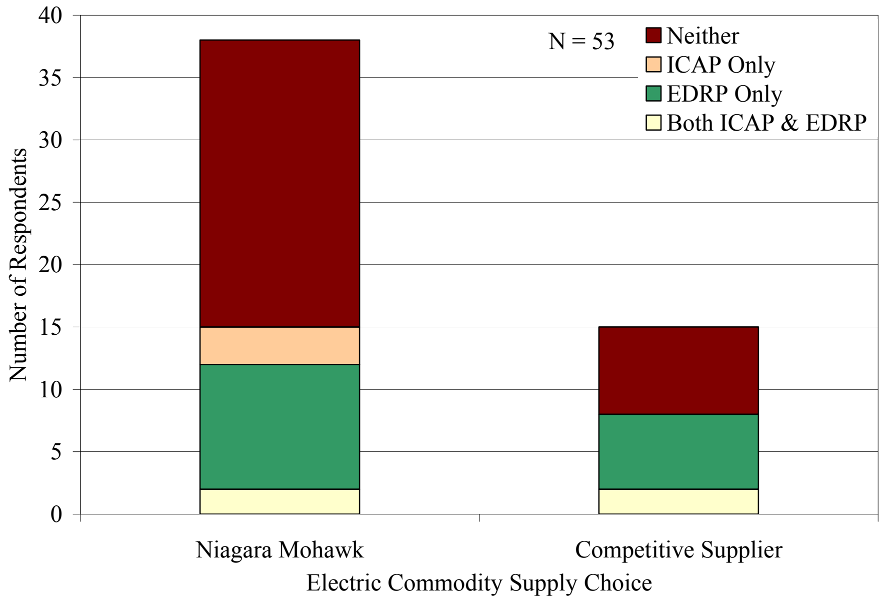
Not surprisingly, a rather strong correlation is observed between stated price response capability and program enrollment (see **Figure 4-18**). 58% of customers who reported an ability to curtail load were enrolled in emergency DR programs. Interestingly, almost 30% of the 28 customers that indicated that they were unable to curtail load were enrolled in NYISO DR programs, and two-thirds of them received payments for load curtailments during events. This suggests that some customers make an important distinction. To them, price response is defined by adjusting hourly usage to SC-3A prices, while curtailing load during a NYISO program event is associated with keeping the electric system secure. The former is considered a business decision undertaken explicitly to avoid high prices, while the latter imparts an intangible but important public service benefit in addition to the payment received. Thus, customers may respond to incentives to curtail on very short notice (two hours for EDRP), but may not exhibit the same response, even to a similar price incentive, when it is posted as the day-ahead SC-3A commodity rate. Our empirical price response results also support this distinction, at least for some industrial customers.

Figure 4-18. Emergency Program Enrollment by Stated Price Response Capability



We examined the relationship of DR-enabling technologies with EDRP and ICAP participation, and found that customers with such technologies installed were more likely to participate, but only slightly so (45% versus 35%). We also find that customers that chose a competitive supplier were more likely to be enrolled in a NYISO emergency program – 53% of ESCo customers have enrolled versus 39% of NMPC customers (see **Figure 4-19**). Many ESCos are active in enrolling customers into the NYISO programs, in part as a way to deliver greater savings over what they can offer for commodity service.

Figure 4-19. Emergency Program Participation by Choice of Supplier



In summary, we observe that the participants in NYISO emergency programs in our sample are almost exclusively non-commercial, with strong participation in EDRP by government/education and industrial customers. The ICAP/SCR participants were exclusively industrial customers.

5. Customer Preferences for Hedging Products

In this chapter, we explore customers' stated preferences for hedging products that vary in how much price variation they are exposed to and the hedging premium that they must pay. To address this issue, customers were asked to complete a conjoint survey as part of the written survey. Respondents were offered a series of *hypothetical* hedging contracts from which they could indicate the ones most preferred.[96] Customers were required to choose many times amongst products differentiated by the levels of their included features. The resulting range of responses makes it possible to derive a statistical representation of the tradeoffs between product features, as well as between levels within these features. This allows us to expand our understanding of customers' preferences for hedging products beyond what was actually offered in the New York market – and may assist policymakers and retail suppliers in designing products with features that are attractive to customers.

5.1 Empirical Specification

In this portion of the survey, customers were given a characterization of their decision environment: a forecast of average day-ahead hourly electricity prices for the next year (~5.7 cents/kWh) and several plots that showed the expected hourly variation in prices. They were then asked to choose among hedge contracts that included a range of values for five different features (see **Table 5-1**) or the SC-3A unhedged alternative.

Table 5-1. Hedging Product Features

Feature	Description	Range
Nominated Load	The percentage of maximum peak demand covered by the hedge contract	• 25% • 50% • 75% • 100%
Covered Hours	The hours of the weekday covered by hedge contract	• 6AM-10PM • 6AM-Noon • Noon-6PM • Noon-10PM
Covered Months	The months of the year covered by hedge contract	• Jun-Aug • Dec-Feb • Jun-Aug & Dec-Feb • All Year
Hedge Method	The type of pricing method used in hedge contract	• Capped Price • Average Price
Hedge Price	The price at which the electric commodity is purchased (¢/kWh) and the total cost of the hedge in terms of the percent of the monthly SC-3A electricity bill (@ X%)	• 6¢ @ 15% • 7¢ @ 10% • 8¢ @ 5% • 9¢ @ 3%

[96] The conjoint survey questions are included in **Appendix B**, following Question 55.

The variable levels were chosen to reflect the range of likely values customers would encounter in the market.[97] Respondents' choices with respect to type of hedging contract was either a capped price (i.e., the price paid can go no higher than the specified cap) or an average price hedge (i.e., the average price paid over the month can go no higher than the specified level) To ensure that the choices forced customers to tradeoff risk and the risk premium, the fifth category of features was constructed as price and premium pairs. The lowest pair represents the average SC-3A commodity prices, which in turn reflects the average NYISO DAM price. This was assigned the highest risk premium, as such a hedge would leave the underwriter with virtually all of the price risk; prices can go much higher, but not much lower. The other pairs were constructed by raising the price by one cent/kWh and lowering the risk premium in a nonlinear fashion, to reflect the assumption that at higher prices the underwriter's relative risk is lower.

Each of the products in the choice sets was characterized exclusively by five separate features; customers could choose one of the four hedge contracts or not purchase the hedge in which case they would remain unhedged on the SC-3A RTP tariff (see **Figure 5-1**).

Figure 5-1. Example Conjoint Survey Choice Set

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 1

	Nominated Load	Covered Hours	Covered Months	Hedge Method	Hedge Price	Check only one choice
Hedge 1	50%	12 Noon - 10 PM	Jun - Aug and Dec - Feb	Capped Price	7¢ @ 10%	
Hedge 2	100%	6 AM - 12 Noon	Dec - Feb	Average Price	6¢ @ 15%	
Hedge 3	75%	6 AM - 10 PM	Jun - Aug	Average Price	9¢ @ 3%	
Hedge 4	25%	12 Noon - 6 PM	All Year	Capped Price	8¢ @ 5%	
None	I wouldn't purchase any of these hedges.					

5.2 Empirical Results

As indicated in **Table 5-2**, 45 of the 53 respondents answered the conjoint survey. About 58% of conjoint respondents (26) reported that they had actually signed up for or purchased a contract that hedged against price risk: NMPC's Option 2 tariff, a physical

[97] Finer granularity to the intervals for the first three variables would be useful in that it allows for a better representation of the shape of the utility functions. However, adding more levels increases the number of choice sets that have to be evaluated.

supply contract with an ESCo, or a financial hedge with a third-party. Thus, our respondents had a fair amount of experience with decisions involving hedging contracts.

Table 5-2. Distribution of Survey Respondents Purchasing Hedges

Option 2	Physical Hedge	Financial Hedge	Survey	Conjoint
Yes	Yes	Yes	0	0
Yes	Yes	—	1	0
Yes	—	Yes	1	1
Yes	—	—	3	1
—	Yes	Yes	5	5
—	Yes	—	11	9
—	—	Yes	3	3
—	—	—	29	26
		Total	**53**	**45**

The results of the estimated conditional logit model are contained in **Table 5-3**. The overall performance of the model is very good. The global test of the null hypothesis (i.e. all coefficients are zero) is soundly rejected as evidenced by the high Chi-Square values and low probability values for three alternative tests of fit, displayed in the lower left hand box of the table. Further, most of the coefficients are significant at the 10% level (a value below 0.10 in the column PR> Chi Sq.) indicating that the survey respondents valued most program features differently.

In interpreting these results, the Utility function measures the marginal change in satisfaction from a change in the level of a single product feature. Utility measures are always relative, thus, the results and relative comparisons for features are independent of this reference point. It is also necessary to understand why only three of the four feature levels are included in the model.[98] To estimate a statistical model in which dummy variables (variables that take on a value of either 1 or 0) are used to indicate different levels of program features, it is necessary to eliminate one level from each set of program features in order to allow the model to be solved.[99] The set of excluded feature levels serves as the basis of comparison for the other levels in the feature and are normalized to have an average utility of zero. As other features levels are substituted, the model recalculates the implied utility, which can be compared to that of the normalized set of features, and the difference represent an improvement in or reduction of utility. Thus, for ease of interpretation, the level within each feature with the lowest estimated utility value was used to construct the normalized "base" feature level. As a result, all other levels within that feature range will produce positive utility improvements.[100] Since all of the

[98] The excluded feature levels are identified in the table with a 0.00 in the parameter estimate, and a 1.00 in the Odds Ratio column.

[99] To simplify, assume amongst three flavors of ice cream, you must chose one from the list of: chocolate, vanilla and strawberry. If a customer didn't like chocolate or vanilla, they must chose strawberry since it is the only option left. If instead a customer liked vanilla the most, they would never chose chocolate or strawberry. Thus, it is possible to describe the entire set of options with only two of the available choices since the third can always be derived from the preferences for the other two. Models with such exact interdependence cannot be statistically estimated.

[100] Using the feature level with the lowest estimated utility value as the "base" level was done for convenience of explanation. Most find it difficult to interpret a negative utility value so by choosing the

estimated coefficients are positive, these feature levels, *ceteris paribus*, are preferred to the "base" program feature levels.

Table 5-3. Multinomial Logit Model Results from Conjoint Survey

Variable	Description	Parameter Estimate	Standard Error	Chi-Square	PR > ChiSq	Odds Ratio
LOAD_1	25% Pk Demand Covered	0.00	-	-	-	1.00
LOAD_2	50% Pk Demand Covered	0.40	0.22	3.21	0.07	1.49
LOAD_3	75% Pk Demand Covered	0.55	0.22	6.01	0.01	1.73
LOAD_4	100% Pk Demand Covered	0.21	0.23	0.80	0.37	1.23
HR_1	6AM-10PM	0.50	0.22	4.96	0.03	1.64
HR_2	6AM-Noon	0.00	-	-	-	1.00
HR_3	Noon-6PM	0.40	0.23	3.08	0.08	1.50
HR_4	Noon-10PM	0.51	0.22	5.27	0.02	1.66
MON_1	Jun-Aug	0.99	0.23	18.86	0.00	2.69
MON_2	Dec-Feb	0.00	-	-	-	1.00
MON_3	Jun-Aug & Dec-Feb	0.45	0.24	3.40	0.07	1.56
MON_4	All Year	0.46	0.25	3.48	0.06	1.59
HDG_1	Capped Price	0.45	0.15	9.04	0.00	1.57
HDG_2	Average Price	0.00	-	-	-	1.00
PRC_1	6¢ @ 15%	0.65	0.22	8.63	0.00	1.91
PRC_2	7¢ @ 10%	0.00	-	-	-	1.00
PRC_3	8¢ @ 5%	0.53	0.23	5.46	0.02	1.69
PRC_4	9¢ @ 3%	0.10	0.24	0.17	0.68	1.10
NO_CHOICE		4.31	0.36	140.55	0.00	74.80

Testing Global Null Hypothesis: BETA=0		
Test	**Chi Square**	**PR >ChiSq**
Likelihood Ratio	1192	< 0.0001
Score	1547	< 0.0001
Wald	880	< 0.0001

Several observations can be made from a comparison of the estimated values of each feature level shown in **Figure 5-2** and Table 5-3:

- **Covered Load:** Respondents preferred a hedge that covers 75% of their peak usage to the other three coverage levels. Interestingly, hedging everything was preferred less than hedging only half the load. Perhaps, these customers realized that to cover the entire peak demand, they would in effect be hedging energy they never use, and consequently prefer a balanced hedge. Accordingly, they found the most value in an option that hedged the bulk of their load (75%), and left the rest exposed to RTP. This may bode well for realizing price response. Since these were customers inclined to leave some peak load exposed, they have an incentive to respond to price increases to reduce the cost of that exposed load.

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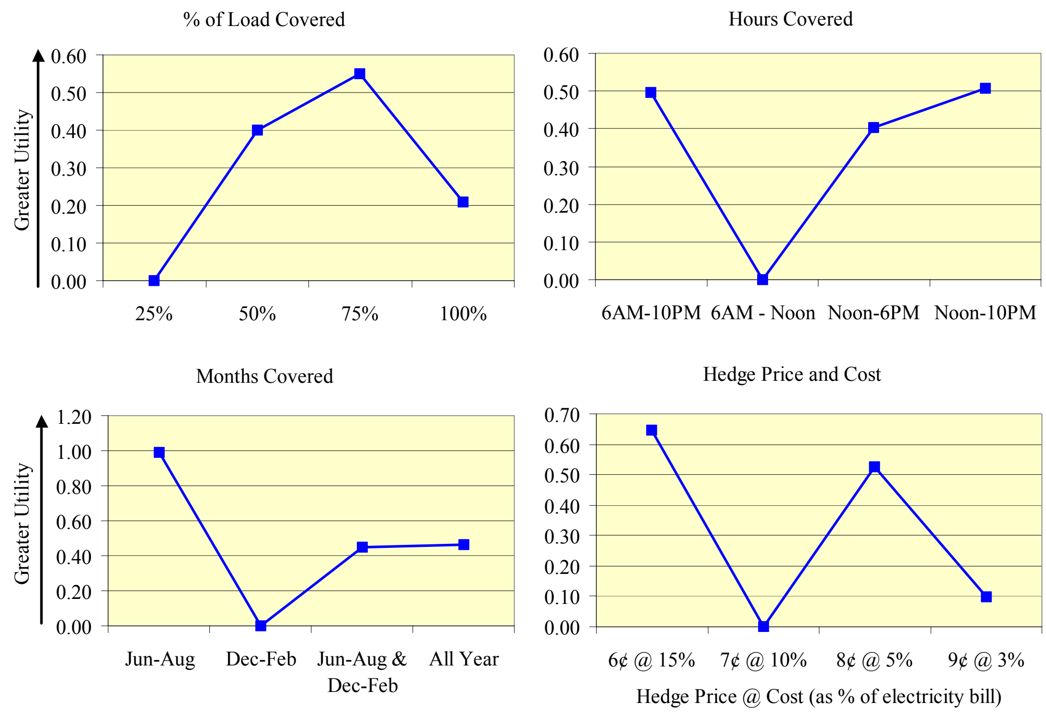
lowest estimated utility level to exclude in each feature, all of the other included feature levels are now guaranteed to have positive coefficient estimates.

Figure 5-2. Relative Utility of Selected Conjoint Survey Features



- **Covered Hours:** Hedge contracts that covered afternoon hours were preferred to ones that only covered morning hours. As illustrated by the approximately equal coefficient estimates, there is little difference in terms of preference for the three different time periods that included the afternoon hours. Customers recognized that high prices were rare in the morning and so shunned any contract that attempted to hedge against this infrequent occurrence.
- **Covered Months:** Respondents greatly preferred summer-only coverage to any other option. However, the hedge that included every month of the year was preferred about as much as a hedge that included both summer and winter, but excluded the spring and fall. This suggests that respondents understood which period of the year high prices are most likely to fall in (summer), and were only interested in hedge contracts that protected them accordingly.
- **Hedge Method:** A capped price hedge was strongly preferred to an average price hedge. Customers seemed far more interested in balancing the benefits of low prices while protecting themselves against price spikes, rather than taking a safer hedged position.
- **Hedge Price:** Paradoxically, respondents assigned roughly the same utility to a 7¢/kWh hedge costing 10% of their monthly bill as to a 9¢/kWh hedge costing 3% as evidenced by the low p-value for this coefficient estimate. The low probability values indicates that utility for the 9¢/kWh@ 3% option is not significantly different from zero, which is the base option level (i.e., 7¢/kWh hedge @10%). If respondents had difficulty in making tradeoffs over such small 1¢/kWh increments, they should have indicated strong preferences for the lowest and highest feature levels and shown ambivalence over the two interior values (i.e. 7¢/kWh @ 10% and 8¢/kWh @ 5%).

The fact that respondents chose a hedge costing 5% and capped at 8¢/kWh over a hedge costing only 3% but capped at 9¢/kWh, is an indication that respondents did not see the 2% lower cost as compensating sufficiently for the extra 1¢/kWh exposure to RTP. The same logic could hold for the observed preference for a very high cost hedge (6¢/kWh @ 15%) over a hedge that cost only 10%, but exposed the holder to 7¢/kWh prices. The fact that customers can make such fine distinctions in balancing risks and the cost to abate them suggests that these customer are quite knowledgeable of the costs associated with price volatility and the nature of that volatility, at least as represented in the conjoint choice sets. Overall, the model estimates suggest that respondents are more willing to pay a substantial amount for a hedge that reduces price spikes altogether, but are relatively less enthusiastic for a hedge that covered only the highest of prices.

5.3 Preferences for Alternative Hedging Products

Using the results from the conditional logit model, we can now examine customers' preferences for hedge products with different features taken from the range of feature levels examined.[101] Substituting in one or more alternative feature levels, a new product utility value is generated, which can be compared to the base value, or any other simulated value. To facilitate comparing alternative hedge products, we introduce the notion of an odds ratio, which is an alternative expression of the underlying utility. The odds ratio indicates the likelihood that a specific product would be chosen compared to some other choice – the higher the odds ratio, the greater the likelihood. For example, an odds ratio of 0.50 means that there is a one in two chance of the outcome (i.e., the choice being made), while an odds ratio of 5 means that the odds are five to one in favor of that choice. As new products are constructed, we can indicate customer preference by setting the odds of that choice being taken given the base product. Alternatively, we can compare new product options to each other using the odds ratio.

Table 5-4. Alternative Hedge Product Preferences Based on Conjoint Results

Program Features	**Hedge Alternative 1**		**Hedge Alternative 2**		**Hedge Alternative 3**	
	Feature Value	**Customer Utility**	**Feature Value**	**Customer Utility**	**Feature Value**	**Customer Utility**
Covered Load	75%	0.55	100%	0.21	50%	0.40
Covered Hours	Noon-10pm	0.51	Noon-10pm	0.51	6am – 10pm	0.50
Covered Months	Jun-Aug	0.99	All Year	0.46	Jun-Aug	0.99
Hedge Method	Price Cap	0.45	Avg. Price	0.00	Price Cap	0.45
Hedge Price	6¢ @ 15%	0.65	9¢ @ 3%	0.10	6¢ @ 15%	0.65
Total Utility		**3.14**		**1.28**		**2.98**
Odds of Hedge vs. SC-3A		**0.31**		**0.05**		**0.26**

[101] Extending the model to feature levels outside the range evaluated is not advisable, as the underlying utility function is calibrated to that set of circumstances defined within the feature range, and it may not apply to extended levels of the features.

A compelling hedging product to consider is one composed of the most preferred individual feature levels as described in Table 5-3. This option is shown as Hedge Alternative 1 in **Table 5-4**.

Note that even this "best of feature" combination still fails to entice respondents off of their existing hourly-differentiated rate structure.[102] Since this hypothetical hedge product contains the feature levels most preferred by our survey respondents, all other possible hedges will provide an even lower utility. This can be seen in the even lower odds ratios for each of the other hypothetical hedge products displayed in Table 5-4. Therefore, the conjoint analysis indicates that, from the features and levels considered, there is not a single hedge product that can be created which respondents would prefer over NMPC's SC-3A rate.

[102] The odds of a respondent choosing this hedge product is 0.31 to 1 – a clear indication that customers prefer to remain with the NMPC SC-3A rate for commodity than purchase this hedge. An odds ratio less than one can be interpreted as a preference for the alternative being considered. For example, in a horse race if the odds of the horse "My Lucky Lady" beating "Sacketts Darling" is 2 to 1, than "My Lucky Lady" is expected to win the race 2 out of 3 times. If, however, the odds of "My Lucky Lady" winning the same race is 0.5 to 1, then the horse "Sacketts Darling" is expected to win the race 2 our of three times. Using odds ratios to identify likely winners and losers is identical to saying that betters prefer one horse to another. In the context of our survey, the later representation of preferences is used.

6. Price Responsiveness

6.1 Overview

In this chapter, we summarize the results of our empirical analysis of SC-3A customers' responsiveness to price changes. We estimated a Constant Elasticity of Substitution (CES) customer demand model, which provides a statistical representation of large customers' response to RTP (see section 2.7.4). We present results of two alternative model specifications that we term *Initial* and *Final* models. The Initial CES model utilizes load and price data for 141 SC-3A accounts, supplemented with customer characteristics information from the NMPC billing system that were readily available. The Final CES model is estimated for a subset of 32 customers for whom additional firm characteristics data were available from the customer survey. The Final CES model also isolates the effects of important customer circumstances, specifically participation in NYISO DR programs during system emergency events.

The average elasticity of substitution for the 32 customers included in the Final CES model is a modest 0.14. Average industrial customer elasticities, estimated at 0.11, are comparable to results of other RTP studies (Herriges et al, 1993; Schwarz et al, 2002). Government/education customers are more highly elastic (0.30) while commercial customers were not price responsive, with an estimated average elasticity of 0.00. We also find that some industrial customers are not very responsive to SC-3A prices (elasticity of 0.03) compared to industrial customers participating in the NYISO EDRP during system emergency events (elasticity of 0.40).

Many customers reported curtailing or foregoing discretionary usage during high-priced periods, which the substitution elasticity does not fully capture. To recognize these behaviors, we employed a Load Response Characterization model (LRC), adapted from Patrick (1990), which provides empirical estimates of the degree to which SC-3A customers shift load from peak to off-peak periods versus conserving energy without increased consumption in off-peak periods. We then combined these results with substitution elasticity estimates to predict the level of DR that can be expected from SC-3A customers during high-price events. At a price of $0.50/kWh, the estimated aggregate demand response from the 141 SC-3A customers is ~100 MW, about 18% of their maximum demand. We conclude by highlighting the implications of these results for the design of RTP programs and indicate areas worthy of further research.

6.2 Initial CES Model Estimates

6.2.1 Model Specification

NMPC supplied load and price data for SC-3A customers for the period from spring of 2000 through the first half of 2003, providing data for an analysis of three full summers.[103] We restricted our analysis to weekdays, focusing on explaining load

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[103] There were a few high-priced hours in the winter months during this period, however, high prices typically occurred during summer months. Consequently, our analysis focused on the three summers for

variation during the most volatile periods.[104] The hours that constitute the peak period depend on the nature of the hourly prices. Thus, we defined and tested three peak (and corresponding off-peak) periods: 2pm to 5pm (Short), 1pm to 5pm (Medium) and noon to 5pm (Long). Within these peak-period definitions, we computed an average load for each customer and a corresponding average SC-3A price for each peak and off-peak period of each day – these were used as inputs in the model.

NMPC customers are also eligible to participate in NYISO DR programs, which offer additional inducements to reduce their electricity bill. Under EDRP, the NYISO declares an emergency event (by giving two or more hours notice) and pays participants the greater of $0.50/kWh or the prevailing, real-time LBMP for curtailments (see section 3.7). This amounts to a uni-directional price overcall: NMPC customers on Option 1 pay the prevailing, day-ahead SC-3A price to consume, but they are paid the NYISO emergency price to curtail.[105] During the study period, the emergency price significantly exceeded the day-ahead market price in every event. Thus, for customers enrolled in EDRP, we replaced the day-ahead SC-3A price with the EDRP payment (typically $0.50/kWh) during event hours to reflect the EDRP inducement.[106]

We also included several other explanatory variables in the Initial CES model that were readily available from NMPC and other secondary sources. We derived a weather-index variable from National Weather Bureau climatic data to account for altered customer response during periods of hot weather.[107] Overall, we expect that as the weather gets hotter, price response will increase as customers have more load available to shift to other times, or do without. However, high temperatures impact customer response in conflicting ways. For example, certain means by which customers respond to high prices, such as reducing space cooling, might become more difficult to sustain on hot days due to increased discomfort.

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which we had complete data: 2000, 2001 and 2002. Usage data was not available for the full period for some customers; where possible, they were included.

[104] Prices during weekends tended to be quite stable, thus, there is no price variability to explain load variations, which do, nonetheless, occur (e.g., economic necessity such as overtime, unusual weather, equipment testing). We found that including weekend days diluted the overall explanatory power of the CES model, and would introduce confounding effects that mask price effects.

[105] This situation is different than a two-part RTP rate, where the marginal price applies only to changes from the CBL. NMPC customers face the SC-3A price for use up to and over the CBL, but if they reduce their load below the CBL during NYISO emergency events, they are paid the emergency price.

[106] During the first two years of EDRP (2001 and 2002), customers could register for both SCR and EDRP in order to receive both a capacity payment for contracted load reductions and an energy payment for actual load reductions. We augmented the SC-3A prices during EDRP event hours for those customers that jointly subscribed to ICAP/SCR and EDRP.

[107] We constructed a categorical temperature heat index variable (THI), that specified whether the day was "hot" as a THI above 70, or not, and accounts for the impacts of relative humidity (see Appendix E, Attachment C).

Figure 6-1. Average Hourly Load of Capital Zone SC-3A Customers by Daily Maximum Price Range (2000)

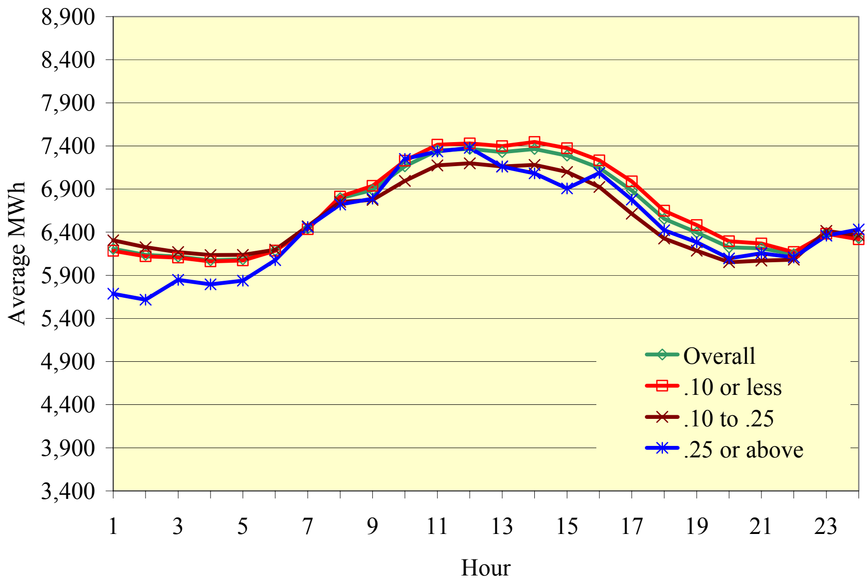
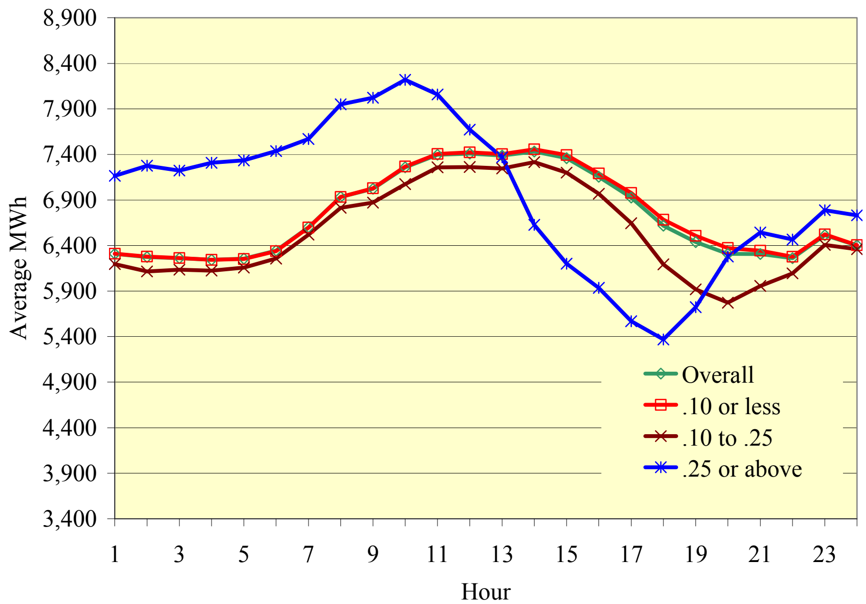
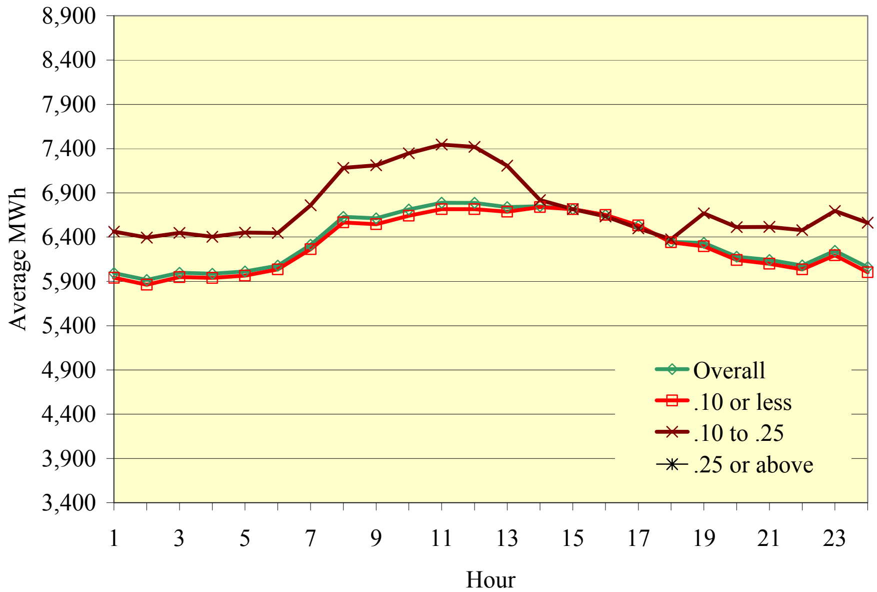


Figure 6-2. Average Hourly Load of Capital Zone SC-3A Customers by Daily Maximum Price Range (2001)



A second explanatory variable was developed to account for yearly differences in price regimes. Average SC-3A prices have been increasing during the study period, while price volatility has been decreasing (see section 3.6). We examined the aggregate SC-3A customer load and price data to see if there were any measurable trends in load response. We observed that the response to high prices (>$0.25/kWh) in 2001 is much more pronounced than in 2000 and 2002, even though there were actually more acute price spikes in 2000. This suggests that consumption patterns in response to prices were somehow altered in 2001 (see **Figure 6-1**, **Figure 6-2**, and **Figure 6-3**). Moreover, the NYISO introduced its DR programs in 2001, which provided SC-3A customers with additional inducements to curtail in real-time, and may have raised customers' overall awareness of market conditions and prices. Thus, it appears that the combination of higher prices and price volatility, and perhaps customers' experiences during 2001, distinguish this year from other years in the study. To capture this factor, we constructed a categorical variable.

Figure 6-3. Average Hourly Load of Capital Zone SC-3A Customers by Daily Maximum Price Range (2002)



We also included type of business as a third categorical variable in the Initial CES model. We postulated that firms could differ in their price response because of different production practices that affect their ability to shift or curtail discretionary usage. We assigned customers to one of four market segments: industrial, commercial, government/education, and other.[108]

A fourth explanatory factor was participation in NYISO DR programs. We hypothesized that customers enrolled in NYISO DR programs were more likely to respond to SC-3A prices due to the monetary inducements provided, a higher level of interest in and familiarity with demand response, and an increased likelihood of having installed DR enabling technologies through NYSERDA programs that targeted NYISO program participants. For ICAP/SCR and DADRP, significant non-compliance penalties would further enhance the incentive to respond. For all three programs (EDRP, ICAP/SCR and

[108] SIC codes, available from NMPC billing records, supported only a classification at the 2-digit level, and in some cases, even that distinction was hard to substantiate. The Other category includes a few customers and was constructed to protect the identity of customers with unique circumstances, given data confidentiality requirements.

DADRP) we introduced categorical variables to establish the impact of participation on price-response. Additionally, recall that we substituted the day-ahead market prices with NYISO emergency prices ($0.50/kWh) during EDRP event hours.[109] This normalizes customer response, treating EDRP payments simply as exaggerated RTP price signals. To the extent that EDRP response is induced by factors other than price, we expect to pick this effect up in the EDRP participation variable.

A fifth factor influencing price response was the type of service customers elected in 1998. We had information on those customers that nominated some portion of their load on Option 2. We created a categorical variable and included any customer that had at any time nominated any portion of their load under the Option 2 contract. We expected that customers on Option 2 would exhibit lowered price response, relative to other customers, because at least some portion of their load was hedged.[110]

Table 6-1. Initial CES Model: Customer Characteristics

Key Attributes *(customers may belong to more than one attribute category)*	
Attribute	**Number of Customers**
Gov't/education	64
Commercial	32
Industrial	43
Other	*
Alt. Supplier	75
Option 2	23
EDRP	29
DADRP	*
SCR	9

Alternative Supplier & Option 2		
Alternative Supplier	**Option 2**	**Total**
No	No	59
No	Yes	7
Yes	No	59
Yes	Yes	16
Total		**141**

* Indicates 3 or fewer customers

NYISO Load Zone	
Zone	**Number of Customers**
West (A)	43
Genesee (B)	9
Central (C)	28
Mohawk Valley (E)	14
Capital (F)	47
Total	**141**

Delivery Voltage Level	
Voltage Level	**Number of Customers**
Secondary	20
Primary	48
Sub-Transmission	49
Transmission	24
Total	**141**

Finally, some customers switched to a competitive supplier during the study period. *A priori*, we hypothesized that customers switched to hedge against the price risks of SC-3A, and as a result were less price responsive. To test this hypothesis, we identified

[109] This approach assumes that ISO DR program incentive *payments* are viewed equivalently by customers as avoided SC-3A prices, which result in *bill savings*. During EDRP events, customers that participate in EDRP also avoid paying the SC-3A rate applicable in those hours for their curtailed load.
[110] Option 2 customers faced the SC-3A price for their marginal usage above the Option II nomination if they did not secure a competitive supplier for that load (see Chapter 4).

customers who had ever taken alternative supply and categorized them with a dummy variable. However, NMPC billing records did not indicate what type of arrangement customers had entered into, so we do not know if they were indeed hedged. Many customers that switched did so to take advantage of the built-in shopping credit, taking contracts indexed to day-ahead market rates or the SC-3A tariff (see section 4.3.3).[111]

Table 6-1 describes the distribution of the 141 customer accounts by business activity, choices for Option 2 and alternative suppliers, location and delivery voltage level.[112]

6.2.2 Model Parameter Estimates

Table 6-2 displays the results of the estimated Initial CES model specification for each of three different peak-period definitions. The "log Inverse Price ratio" estimates represent the "base case" substitution elasticity.[113] The estimates for the other variables indicate how they influence customers' elasticity, so their parameters are additive to the base elasticity estimate.

Overall the model fit is good. The R-squared values for the three peak periods range from 0.54 to 0.63, implying that the model specification accounts for a substantial amount of the load variation. The test for overall significance produces an F-statistic that is significant at the 1% level in all three peak-period models, indicating that the estimated regression coefficients are not all jointly equal to zero.

Temperature and the year 2001 (the highest priced year in the study period) were found to have a very small and in most cases insignificant effect on usage. This might be because these variables are highly correlated with other explanatory variables, and therefore no unique impact is quantifiable.

The elasticity values for the three business sectors are the sum of the base-case elasticity and the specific sector parameter estimate.[114] For example, using the 2-5 pm model estimates, the industrial sector elasticity is the sum of the Log Inverse Price Ratio variable coefficient (-0.05) and the industrial variable (0.14), resulting in an elasticity of 0.09. Accordingly, the substitution elasticity estimate for commercial customers is 0.10 and for government/education it is 0.18. Recall that the substitution elasticity is expected to have a positive value.

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[111]Each explanatory variable included in the Initial CES Model is multiplied by the log of the inverse price ratio to produce a shift in the slope of the demand equation, which adjusts the estimated elasticity value (see Appendix E for more details).

[112] These last two factors do not require explicit recognition in the CES model because the SC-3A prices incorporate both directly.

[113] In a dummy-variable regression model, the coefficient on the Log Inverse Price Ratio represents observations that have a zero for all of the included categorical variables. For the initial CES model, this means that the "base case" is a customer classified as Other, who never took NMPC Option 2 or switched to a competitive supplier, and who never enrolled in NYISO DR programs. The "base case" also represents non-"hot" days in the summers of either 2000 or 2002, since these categorical variables are also included in the Initial CES model.

[114] The Other sector parameter is represented by the coefficient on the Log Inverse Price Ratio variable.

Table 6-2. Initial CES Demand Model Parameter Estimates

N = 141	Peak Period		
	2 pm – 5 pm	**1 pm – 5 pm**	**Noon – 5 pm**
Log Inverse Price Ratio (base-case estimate)	-0.05	-0.08	-0.11***
Temp > 70	-0.02**	-0.01	-0.01
Year=2001	0.01**	0.01	0.01
Industrial	0.14**	0.12**	0.13**
Commercial	0.15**	0.14**	0.15**
Government/education	0.23*	0.19*	0.18*
Alternative Supplier	-0.10*	-0.06*	-0.03**
Option 2 Customer	0.07*	0.06*	0.07*
NYISO EDRP Participant	0.03**	0.02	0.02
NYISO DADRP Participant	0.29*	0.31*	0.21*
NYISO ICAP/SCR Participant	0.20*	0.15*	0.14*
R-Squared	0.54	0.59	0.63
F-Test of Global Significance	205*	254*	297*

* = Significant at 1% level
** = Significant at 5% level
*** = Significant at 10% level
Values less than 0.005 appear as 0.00 due to rounding

The influences of the other variables are interpreted by adding their effect to the appropriate business sector effects. For example, again using the 2-5 pm estimates, an industrial customer that has switched to a competitive supplier would have an estimated elasticity of -0.01 (the 0.09 industrial customer elasticity is reduced by 0.10). In other words, customers that switched to competitive suppliers were markedly less price-responsive than those who stayed with NMPC. This may be because these customers left SC-3A service to acquire a hedge against market prices, and having done so are no longer inclined to respond to prices. Alternatively, they may have switched explicitly to avoid worrying about price volatility. All other things equal, switching reduced price response.

In contrast, customers that elected the Option 2 (take-or-pay hedge) contract were slightly more price-responsive; 0.07 is added to the business sector base value to arrive at the applicable substitution elasticity estimate for these customers. This result, which is highly significant, does *not* comport with our initial hypothesis that such customers sought a hedge to escape price volatility. However, Option 2 customers typically covered only about 60% of their peak load and many were on SC-3A Option 1 for their residual load (see section 4.3.1). Thus, many were exposed to SC-3A price volatility for their marginal usage and it appears that these customers were indeed price responsive.

The coefficients for NYISO program participation are all positive and significant, although the effect for EDRP is a factor of ten lower than for ICAP/SCR and DADRP. We expected that customers in the capacity (SCR) and economic (DADRP) programs would be more elastic, since these programs impose penalties for noncompliance. But we expected EDRP participants to be similarly elastic, as they are offered an extra inducement to curtail, albeit with only two hours notice. We employed alternative specifications in the Final CES model that differentiated price response during event and non-event days in order to explore this issue further.

With regard to the alternative peak period specifications, the coefficient estimates are relatively stable across the three peak time periods with little change in significance levels (Table 6-2). The elasticity of substitution values generally decrease when the peak period is defined to include more hours. The Long peak-period specification has the most explanatory power (the highest R-square value); thus, we primarily present model results using this peak period definition (12-5 pm).

6.2.3 Substitution Elasticities

In **Table 6-3**, we present estimated elasticity values for different customer groups. The average elasticities (with all applicable influences included) are relatively modest for the noon-5pm peak period: industrial (0.04), commercial (0.04), government/education (0.08), and other (-0.11).[115] The overall, load-weighted average elasticity for all 141 customers is 0.06, which is somewhat lower than that found in other studies of RTP program response.[116] Estimated elasticity values for individual customers range from a low of -0.13 (other customers; all peak definitions) to a high of 0.38 (industrial, 2pm-5pm peak).

Table 6-3. Initial CES Model: Elasticity of Substitution by Business Classification

Business Classification	N	% of Total Maximum Demand	Peak: 2PM - 5PM		Peak: 1PM - 5PM		Peak: 12 Noon - 5PM	
			Range	**Avg.**	**Range**	**Avg.**	**Range**	**Avg.**
Industrial	43	34%	0.01 – 0.38	0.09	-0.01 – 0.32	0.05	-0.01 – 0.23	0.04
Commercial	32	21%	0.02 – 0.25	0.07	0.02 – 0.18	0.05	0.01 – 0.16	0.04
Gov't/education	64	44%	0.1 – 0.28	0.16	0.07 – 0.19	0.10	0.05 – 0.16	0.08
Other	*	1%	-0.13 – -0.02	-0.07	-0.13 – -0.06	-0.09	-0.13 – -0.09	-0.11

* Indicates 3 or fewer customers

In **Table 6-4**, we provide estimated substitution elasticity values for several categorical variables (participation in NYISO DR program, Option 2 and competitive supplier choices). These more detailed estimates provide greater insight into the parameter estimate effects shown in Table 6-2. For example, participation in a NYISO DR program results in larger substitution elasticity for industrial customers, by a factor of almost four. However the difference in substitution elasticities is very small for government/education customers. These results suggest that NYISO program participation is not the motivating factor that distinguishes firms within the government/education sector.

[115] Overall, *positive* net values are consistent with the CES model specifications, while *negative* elasticity values indicate some sort of misspecification.
[116] For example Schwarz et al, 2002 reports an overall substitution elasticity of about 0.12.

Table 6-4. Initial CES Model: Elasticity of Substitution for Several Categorical Variables

Elasticity of Substitution by Business Classification and NYISO DR Participation					
Business Classification	**NYISO DR Participation**	**N**	**% of Total Maximum Demand**	**Peak: 12 Noon – 5PM**	
				Range	**Avg.**
Industrial	No	31	17%	-0.01 – 0.03	0.02
Industrial	Yes	12	18%	0.01 – 0.23	0.09
Commercial	No	28	18%	0.01 – 0.12	0.04
Commercial	Yes	4	3%	0.02 – 0.16	0.06
Gov't/education	No	50	37%	0.05 – 0.15	0.08
Gov't/education	Yes	14	7%	0.06 – 0.16	0.09
Other	No	*	0%	-0.13 – -0.13	-0.13
Other	Yes	*	1%	-0.09 – -0.09	-0.09

Elasticity of Substitution by Business Classification and Option 2 Status					
Business Classification	**Option 2 Customer**	**N**	**% of Total Maximum Demand**	**Peak: 12 Noon – 5PM**	
				Range	**Avg.**
Industrial	No	39	30%	-0.01 – 0.23	0.03
Industrial	Yes	4	5%	0.07 – 0.15	0.11
Commercial	No	24	16%	0.01 – 0.05	0.03
Commercial	Yes	8	5%	0.08 – 0.16	0.10
Gov't/education	No	53	37%	0.05 – 0.14	0.07
Gov't/education	Yes	11	7%	0.12 – 0.16	0.13
Other	No	*	1%	-0.13 – -0.09	-0.11

Elasticity of Substitution by Business Classification and Alternative Supplier Status					
Business Classification	**Alternative Supplier Status**	**N**	**% of Total Maximum Demand**	**Peak: 12 Noon – 5PM**	
				Range	**Avg.**
Industrial	No	27	24%	0.03 – 0.23	0.06
Industrial	Yes	16	11%	-0.01 – 0.07	0.00
Commercial	No	11	7%	0.05 – 0.16	0.06
Commercial	Yes	21	14%	0.01 – 0.08	0.03
Gov't/education	No	27	21%	0.08 – 0.16	0.10
Gov't/education	Yes	37	23%	0.05 – 0.12	0.07
Other	No	*	1%	-0.09 – -0.09	-0.09
Other	Yes	*	0%	-0.13 – -0.13	-0.13

* Indicates 3 or fewer customers

The increase in average elasticity of substitution values due to Option 2 selection is pronounced for all three business types. Average elasticity values are lower for all types of customers that selected a competitive supplier over NMPC default service.

The Initial CES model provides an encouragingly good statistical fit in terms of its R-Squared value and tests for significance of the parameters as a set. The model produced some surprising results, most notably that on average, government/education customers are the most price-responsive. We have concerns about several aspects of the Initial CES model specification: 1) that the alternate supplier status variable does not differentiate by type of contract (e.g. hedged vs. indexed) so that it is difficult to interpret the results, and 2) that there are omitted variables related to firm-level circumstances that may account for important variations in usage but are not represented in the model, thereby masking differences among customers circumstances in price response.

6.3 Final CES Model

In the *Final* CES model, we tested a number of variables derived from customer survey responses. Our goal was to see if additional, in-depth information about customer circumstances would provide for a more robust characterization of electricity usage and better identify important drivers to price response that can be used for policy evaluation and subsequent program implementation.

6.3.1 Model Specification

Many of the survey-derived variables proved to be insignificant in explaining differences in groups and were omitted.[117] However, the following variables provided important explanatory information and were included in the Final model:

- *Time of Peak Usage*. Survey responses regarding the timing of customers' peak loads were used to design an alternative indicator of shifting ability – whether a customer's peak usage occurs between noon and 5 pm, or at some other time of day. We posited that afternoon-peaking customers were less able to respond to peak prices that occurred coincident with their most intense business and process constraints.
- *Relative importance of electricity costs*. Survey respondents' assessment of their electricity costs as a percent of annual operating costs was also assigned to a variable. Customers were sorted according to whether they reported electricity costs less than 10% or 10% or more of operating costs. We postulated that customers that are more electricity intensive are less able to respond to peak prices.
- *Investments in DR-enabling technologies*. We posited that customers that had invested in various DR-enabling technologies that could help them shift load would be more price responsive. A dummy variable was constructed to reflect whether the customer had made such investments after the start of the RTP-based SC-3A service in 1998 and another dummy variable for similar investments prior to 1998.[118]

[117] In some cases the variables provided redundant measures to factors already included. In others, the hypothesized effect was not forthcoming in terms of a parameter estimate that was statistically significant.
[118] In creating the dummy variable for investments in DR enabling technologies, customers that invested in process/building automation systems, control devices on specific equipment or processes, or peak load management control devices were coded as "1"; other responses were coded as "0" (see question 31 in survey)

- *Participation in NYISO EDRP*: We also constructed an additional dummy variable to better sort out the influence of participation in the EDRP program (beyond just enrollment). To isolate the impact of these additional inducements to curtail, the dummy specification distinguished between EDRP event days and other "non-event" days, thereby allowing for the elasticity of EDRP participants to vary according to whether the customer faced SC-3A prices or was provided an additional inducement ($.50/kWh) to curtail. Our hypothesis was that the extra inducement would increase price response over that induced by SC-3A prices alone. During the summers of 2000-2002, there were five NYISO EDRP event days.

In the Final CES model, we omitted two variables that were included in the Initial model: the "Option 2" and "Competitive Supplier" variables. The coefficients for Option 2 customers were positive in the Initial model. This is somewhat counter-intuitive as we expect Option 2 to reduce customers' responsiveness, not enhance it. However, as discussed in Chapter 4, there were wide variations in how much peak and off-peak load these customers actually hedged over time, but we found no way to convey this information in the CES model specification. Additional analyses, augmented with more customer-supplied information, might allow for the specification of a variable that would characterize how the Option 2 choice contributes to customers' inclination, or aversion, to respond to prices. Similarly, the Competitive Supplier variable doesn't distinguish between types of supply arrangements (flat versus indexed rates); we believe that a better specification of exactly what kind of service the alternative supplier offered during various time periods is required in order to measure the impact of competitive supply on price response.

Table 6-5. Final CES Model: Customer Characteristics

Attribute	**Number of Customers**
Government/education	11
Commercial	9
Industrial	10
Other	*
Peak Usage Noon-5pm	16
Electricity Costs > 10% Operating Costs	15
Investment made prior to RTP	20
Investment made while on RTP	13
EDRP	10
DADRP	*
SCR	*

*indicates 3 or fewer customers

Zone	**Number of Customers**
West (A)	8
Central (C)	9
Mohawk Valley (E)	5
Capital (F)	10

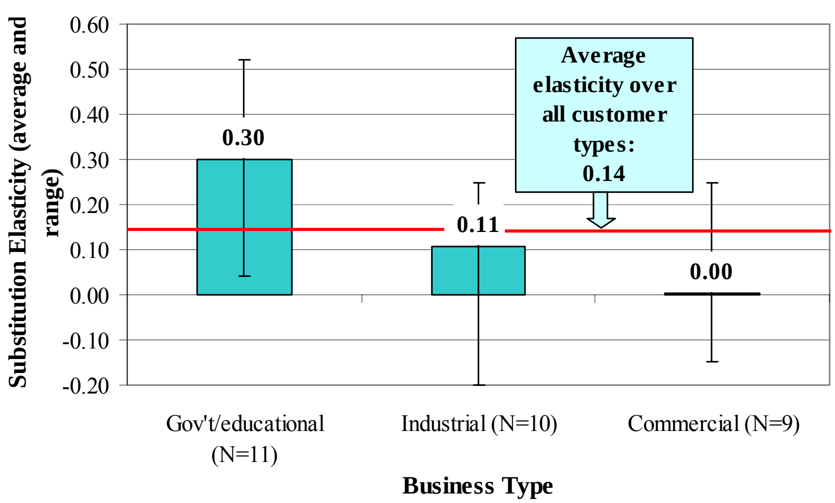
Delivery Voltage Level	**Number of Customers**
Secondary	5
Primary	11
Sub-Transmission	9
Transmission	7

Hourly price and load from 32 customers were used to estimate the Final response models.[119] This reduction in sample size resulted from the pattern of survey responses; only those customers that answered *all* the relevant questions could be analyzed.[120] Nonetheless, overall, the remaining customers appear to be fairly representative of the population from which they came. **Table 6-5** displays the distribution of responses for the 32 customers included in the Final CES model analysis.

6.3.2 Model Results: Substitution Elasticity

The average load-weighted substitution elasticity, computed over all 32 customers for whom we had adequate survey data for modeling, is a modest 0.14. This means that a 100% change in the inverse price ratio (off-peak price/peak price) results in a 14% change in the ratio of peak/off-peak electricity consumption.[121] This load-weighted average value includes all business categories, customer circumstances, and other influences and is about double the elasticity value estimated in the Initial CES Model. Overall the model explained about 25% (R^2) of the variation in customers' peak usage ratio over the three summer periods. Because there are only about 25% as many customers in the Final CES model as were used in the initial specification, a lower R^2 is to be expected.

Figure 6-4. Substitution Elasticities for 32 SC-3A Customers by Business Type



[119] We used dummy variable slope shifters to distinguish differences in elasticity among the three business sectors (Government/education, industrial, Commercial) thereby allowing for an individual substitution elasticity estimate for each sector and to reflect enrollment in NYISO DR programs.

[120] In order to include answers to a survey question in the estimated demand equations, survey respondents had to provide a definitive answer: either a "Yes" or a "No". A choice to not respond to the question, which was an option on every question, provides no information concerning classification of the explanatory variable and thus, that customer was omitted from the final CES model sample.

[121] Assuming that typical SC-3A off-peak and peak prices are \$0.04/kWh and \$0.06/kWh, the associated off-peak to peak price ratio is 1:1.5. A 100% change in that ratio (to 1:3) would result if the peak price rose to \$0.12/kWh.

However, computing elasticities for each customer group reveals substantial variation, both within and between business categories (**Figure 6-4**). Average industrial customer elasticities, estimated at 0.11, are comparable to results of other RTP studies (Herriges et al, 1993; Schwarz et al, 2002). Government/education customers are more highly elastic (0.30), which refutes the common perception that only industrial customers are good candidates for price response. On average, commercial customers were not price responsive (0.00).[122]

The average elasticities mask important differences in price response associated with customer circumstances. To illustrate these effects, we estimated substitution elasticities in a disaggregated fashion, first by business sector and EDRP participation, to establish a base price response, and then we estimated the marginal impact of customer circumstances and other influences on elasticities (see **Figure 6-5**).[123]

Figure 6-5. Impact of Characteristics and Circumstances on SC-3A Customers' Substitution Elasticities

Base Substitution Elasticity Estimates

Average Values for Customer Groups		EDRP Participation?		
		No	Yes	
			Event Day?	
			No	Yes
Business Type	Gov't/education	0.5	0.40	0.34
	Commercial	0.26	0.18	0.06
	Industrial	0.24	0.03	0.40

Additive Impact of Other Influences

Additional Circumstances	If "yes", increment base elasticity by…
Customer factors	
Is the customer a participant in…	
...DADRP?	adding 0.33
...ICAP/SCR?	adding 0.16
Is the customer's peak usage between 12 noon and 5pm?	subtracting 0.19
Does electricity account for >10% of operating costs?	subtracting 0.08
Did the customer install DR-enabling technologies…	
...before 1998?	subtracting 0.11
...after 1998?	subtracting 0.04
Other influences	
Is the daily peak temperature higher than 70 degrees?	adding 0.02
Is the year 2001?	no effect

The first table in Figure 6-5 displays base elasticities for cohorts of SC-3A customers disaggregated by business type and EDRP participation, without adjustment for any other customer-specific circumstances or factors. For EDRP participants (rightmost two

[122] Note that there is greater variation among the average elasticity values for the three customer groups compared to the Initial CES Model results, which we believe is attributable to the inclusion of customer-specific factors.
[123] The model parameter estimates for the three peak periods are included in Appendix E.

columns in the table) base elasticities are computed for both event and non-event days.[124] On non-event days, EDRP participants face only SC-3A prices.

Under most circumstances, government/education customers are significantly more price responsive than other customer groups; this is consistent with the average elasticity values reported in Figure 6-5. However, on EDRP event days, government/education EDRP participants are ~30% less price elastic than non-participant government/education customers. This may indicate that these customers have already curtailed or shifted load in response to SC-3A day-ahead prices when the NYISO calls an EDRP event, leaving limited opportunities to shed additional load, even at the higher EDRP inducement price. This explanation is based on the notion that some customers have a maximum amount of curtailable load.[125]

Industrial customers enrolled in EDRP, on the other hand, show dramatically higher price response during EDRP events compared to industrial customer response to SC-3A prices alone: 0.40 substitution elasticity during EDRP events vs. 0.24 for customers not enrolled in EDRP and 0.03 for non-event days for industrial customers enrolled in EDRP. For these customers, the EDRP program appears to entice price response that SC-3A prices do not.

The second set of results in Figure 6-5 shows the impact of additional factors on SC-3A customers' responsiveness that are additive to the base elasticities in the first table.[126] These values are the model parameter estimates for the Final CES model. These results indicate that participation in other NYISO DR programs (DADRP and ICAP/SCR) enhances price response (the base elasticities are increased by 0.33 and 0.16 respectively). This is not surprising, since both programs provide additional financial incentives to curtail and assess penalties for non-compliance.[127] The DADRP estimate suggests that the prospect of getting paid to curtail boosts customer response over that which would be forthcoming from SC-3A prices alone.[128]

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[124] During the study period, there were five days when the NYISO activated the EDRP program. On such days, during event hours, EDRP participants were assumed to face the $0.50/kWh curtailment incentive paid by the program as their SC-3A "price".

[125] Typically, EDRP events are preceded by high day-ahead market prices, which are the basis for SC-3A prices. The model we employed assumes that elasticity is constant at all prices; thus computed elasticities may be lower if prices continue to increase after customers have reached their maximum load-shedding capability than they would be for the same load response at lower prices. Further research using demand models that do not impose this constant-elasticity constraint, augmented by customer interviews on their curtailment potential, may help resolve this apparent paradox.

[126] For example, if a particular industrial customer were not enrolled in EDRP, its base elasticity would be 0.24. If that customer were a participant in the NYISO ICAP/SCR program, its elasticity would be augmented by 0.16 to 0.40. If that same customer experienced its peak load in the afternoons (-0.19) and had made technology investments since 1998 (-0.04), the resulting elasticity for that customer would be 0.17.

[127] ICAP/SCR allows customers to sell their curtailment capability to a load-serving entity to meet its installed capacity requirement. Customers receive an energy payment for their load reduction if called. Failure to comply with curtailment events can result in financial penalties and a de-rating of the curtailable load the customer can sell in the future.

[128] DADRP allows customer to bid curtailments into the NYISO day-ahead market, and if scheduled, receive the day-ahead market price if they curtail as scheduled the next day. In effect, they get paid to

Customers that report peak usage between noon and 5pm and those with high electricity intensity are less responsive than other customers, all else equal (substitution elasticities are reduced by 0.19 and 0.08 respectively). This is consistent with the notion that it is harder for customers to curtail when critical business activity and electric use coincide with times of high prices.[129] Note that subtracting these amounts from the base elasticities above for the three business sectors still leaves positive elasticity values overall.

However, the technology investment results are counter-intuitive. The negative marginal elasticities indicate that investing in DR-enabling technologies actually decreases price responsiveness. This effect is much more pronounced for DR investments made before 1998. For investments made after 1998, the negative impact on elasticity is small, but we would expect these DR-oriented investments to facilitate price response. It may be that customers have received peak load management devices or information systems from NMPC or through NYSERDA public benefit programs, but have not taken full advantage of their capabilities. Many customers reported that they made energy information system (EIS) investments in an attempt to better understand the overall load profile at their facility, not to expressly improve their ability to be price-responsive. Information from EIS and EMCS were often used to reduce overall electricity consumption as well as reduce usage during peak periods.[130] Another possibility is that the equipment was installed relatively recently so that it was not available during the period covered by our demand modeling.[131] Finally, investments in DR-enabling technologies may be correlated with other factors that reduce price response but are not accounted for in the model. Further research is needed to more clearly specify the impact of technology on price response.

The last two factors, temperatures over 70 degrees Fahrenheit and the year 2001 (characterized by much higher price volatility), have negligible incremental impacts on customers' elasticity.[132]

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respond to prices that are themselves an inducement to respond, which some argue is a double payment. However, these results suggest that customers treat the two situations differently when it comes to adjusting usage.

[129] However, other studies of industrial response to RTP have found the opposite result: that customers with more electricity-intensive production tend to be more, not less, responsive (Christensen Associates, 2000).

[130] In addition, the decision to invest in enabling DR technologies is assumed to be exogenous (i.e., independent) of price-responsiveness in our model specification. Many believe that customers invest in technology because they already are savvy about their electricity demands. To mitigate the possible effects of this assumption, a choice model could be developed to predict investment in energy management equipment, the results of which would be included in the model as a truly exogenous explanatory variable. Time and resources did not permit such activities in this phase of the analysis, but is a subject for continuing research in this area.

[131] NYSERDA implemented programs beginning in 2001 that provided incentives to customers to install technologies that would assist them in responding to the NYISO demand response programs. However, many projects were not operational until the summer of 2002 so the cumulative impact is not reflected in the modeled data.

[132] Because hot days are often associated with high day-ahead prices and EDRP and ICAP/SCR events, isolating a separate heat effect is difficult.

In summary, the average estimated business class elasticities belie the diversity of response among customers within the same business classifications. Some customers are very responsive, while many do not appear to adjust their usage to prevailing SC-3A prices. Participation in the NYISO EDRP program has a positive influence on the response of some industrial customers that display little response to SC-3A prices alone. Other NYISO DR programs also appear to increase response, lending support to the notion that RTP and DR programs are complementary.

6.3.3 Quantifying Load Shifting vs. Conservation/Curtailment Behavior

The CES demand model assumes that customers shift electricity-consuming activities from the peak period to the same day's off-peak period and measures response in terms of load shifting by comparing changes in the *ratio* of peak to off-peak consumption. However, many customers reported curtailing or foregoing discretionary usage during high-priced periods without making it up later. In such cases, the estimated elasticity of substitution underestimates the nominal level of the reduction in peak usage because the response of customers that curtail or conserve load is not fully captured.

To adjust our characterization of price response to recognize these behaviors, we adapted a model introduced by Patrick (1990), which we call a Load Response Characterization (LRC) Model (see section 2.7.5). The LRC model distinguishes load shifting from foregoing discretionary consumption, which Patrick (1990) defines as conservation. A conservation behavior parameter is estimated from customers' hourly electricity usage data to express the degree of foregone consumption relative to a customer baseline (CBL). This parameter ranges in value from zero (complete shifting) to one (complete conservation). Values between these extremes indicate combinations of shifting and discretionary peak reductions. The full specification for the LRC method of empirically characterizing customer price response behavior is described in **Appendix E.**

The LRC model serves two purposes in this study. First, combined with survey data, it allows us to better understand the type of response undertaken on a high priced day by different types of customers – information that can help guide RTP and technology adoption program design. Second, it also allows us to apply the CES model results more accurately in predicting load response due to individual price events. In this section, we deal with the former – characterizing customer response behavior. In the next section, we predict SC-3A customers' aggregate response to price events by combining CES and LRC model results.

In order to estimate the LRC model, we had to define and compute a CBL using available load data from SC-3A customers.[133] We hypothesized that SC-3A customers see the

[133] In order to assess the extent to which customers shift load or forego usage, some estimate of "typical" or expected electricity consumption must be known to assess the effects of load responding to price. In two-part RTP programs, utilities establish a customer baseline (CBL), which reflects a customer's historic hourly consumption pattern. For NMPC SC-3A customers, we had to construct a CBL from recent load data, because we did not have access to usage data prior to 2000 and because NMPC did not calculate a CBL, given the one-part rate design.

prices they pay as belonging to two basic regimes: a low-priced, typical regime and an episodic, high-priced regime. We assumed that customers adopt relatively consistent usage patterns over time for the low-priced regime, and that the high-priced regime represents opportunities to reduce their electricity costs if some usage can be curtailed or shifted. For our purposes, we define "low-priced" days as days in which SC-3A peak period prices (from noon to 5pm) never reached $0.075/kWh; all other days (those with peak-period prices above $0.075/kWh), are deemed "high-priced" days.[134] Usage on the low-priced days is averaged in each hour to define the CBL, which is then compared to the average hourly usage on high-priced days.

We further refined the CBL by subdividing the low-priced days into "hot" and "cool" days, in an attempt to separate weather from price effects.[135] This seemed appropriate given that many survey respondents indicated that their electricity usage is weather-sensitive and because these customers do indeed exhibit systematically different consumption patterns on hot and cool days. We used the median of the average Temperature Heat Index (THI) derived by the National Weather Service during the hours of noon to 5pm to segment and distinguish hot from cool days. We also disaggregated the CBL days by year, thus allowing the CBL to differ across time and weather in order to represent changes in business activity that might take place from year to year and from hot days to cool days. **Table 6-6** shows the number of CBL and high-priced days assigned to these categories.

Table 6-6. Customer Baseline (CBL) and "High-Priced' Days by Year and Temperature

Year	Number of CBL Days		Number of High-Priced Days	
	Hot	Cool	Hot	Cool
2000	19	19	18	11
2001	17	29	19	2
2002	6	28	24	7

We then derived individual customers' CBL usage by taking the average consumption for each hour of the day over all days in each category. This allows us to compare each customer's consumption on high-priced days with their consumption on similar CBL days and to estimate how they are responding (see Appendix E). To add explanatory power to the LRC model, we used the same set of exogenous variables and peak periods that were tested and/or included in the Final CES demand model.

The estimated coefficients of the final LRC model are displayed in **Table 6-7**. The model is able to explain over 85% of the variation in daily electricity use from the constructed

[134] Of course, our determination of high and low prices is subjective and may not exactly mirror how individual customers' view them.

[135] By defining the CBL in this way, we are assuming that if all hourly prices during a particular "weather" day are below the threshold price of $0.75/kWh, there is no incentive for customers to alter usage in response to the relatively minor differences in hourly prices. In contrast, when the price differentials are somewhat higher, there is an incentive to alter electricity usage in response to price.

baseline. Globally, the parameters are statistically significant and the majority of the estimated parameters are individually significant at the 99% level. The results for the Long peak period are shown in Table 6-7; results were similar for the other peak-period definitions.

Table 6-7. Load Response Characterization Model Parameter Estimates

Parameter	**LRC Estimate (noon-5pm peak)**
% Change in Peak Use to CBL	0.83*
Peak Usage Noon-5 PM	-0.04***
Government/education	-0.15*
Commercial	-0.12*
Industrial	-0.17*
Electricity Cost > 10% Op Cost	-0.02
Investment made prior to RTP	0.26*
Investment made while on RTP	0.06*
NYISO EDRP Participant	0.29*
NYISO DADRP Participant	-0.51*
NYISO SCR Participant	-0.35*
R-Squared	0.87
F-Test of Global Significance	363.88*
N=32 * Significant at 1% level ** Significant at 5% level *** Significant at 10% level	

To interpret the coefficients, it is convenient to look at the sign of the estimated parameters. A positive sign indicates customers with the given characteristic are more inclined to forego electricity throughout the day on high priced days, while a negative sign indicates customers with the given characteristic are more inclined to shift usage from peak to off-peak periods on high-priced days. For example, customers who made investments in DR equipment prior to seeing hourly prices on the SC-3A RTP rate tended to more universally reduce and curtail load in both periods. This type of response behavior is also exhibited by customers that made investments in DR enabling technologies after 1998, but to a lesser degree (coefficient values are 0.26 and 0.06 respectively). Interestingly, EDRP participants tend to forego electricity in more equal proportions across the day while DADRP and SCR participants overwhelmingly appear inclined to consume disproportionately in the peak than they use throughout the day.

Table 6-8 displays the estimated conservation parameters for SC-3A customers by business category for the noon to 5pm peak period. Average sector-specific values range from 0.85 (industrial) to 0.91 (commercial), confirming survey results indicating that customers primarily curtail discretionary usage rather than shift load. The estimate ranges in Table 6-8 bound the results within each business classification.[136]

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[136] Parameter estimates greater than 1.0 indicate that the customer reduces load by a greater proportion in the off-peak period than is curtailed (foregone) in the peak period.

Table 6-8. Final LRC Model: Conservation Parameter Estimates

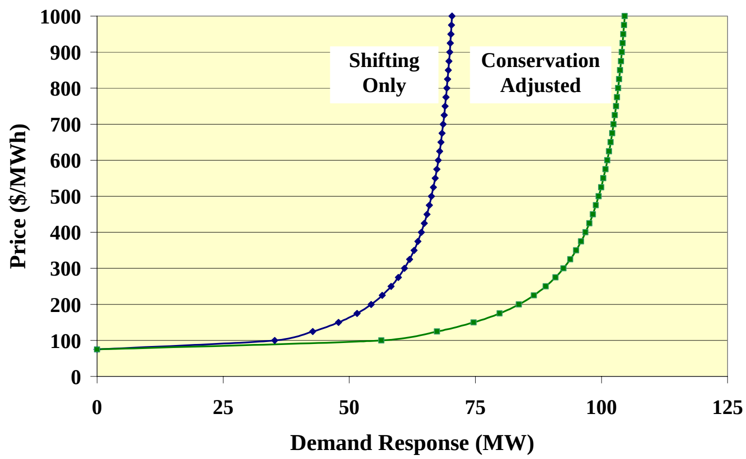
Business Type	Number of Customers	% of Total Maximum Demand	Average Conservation Coefficient	Estimate Range
Industrial	10	52%	0.82	0.50 – 0.92
Commercial	9	23%	0.91	0.64 – 1.00
Gov't/education	11	21%	0.85	0.64 – 1.09

6.4 Aggregate Demand Response Potential of SC-3A Customers

We used substitution elasticity and conservation parameter estimates to predict the level of demand response that can be expected from high-price events. This provides a comprehensive estimate of the aggregate response of SC-3A customers that accounts for both types of curtailment behavior.

To estimate the peak-period price response of SC-3A customers as a group, the elasticities for the four business sectors were extrapolated to the population of SC-3A customer accounts, using sector load weights.[137] **Figure 6-6** illustrates the resulting peak period curtailment curves, first using the estimated substitution elasticities alone (shifting behavior), and then incorporating the estimated conservation effect. At a reference price of \$0.50/kWh, almost 30 MW of additional demand response is attributable to curtailing or foregoing discretionary usage. Over 90% of the curtailment potential is achieved at a price of \$0.50/kWh. The maximum curtailment amounts to about 18% of the non-coincident peak demand of the SC-3A customer class.[138]

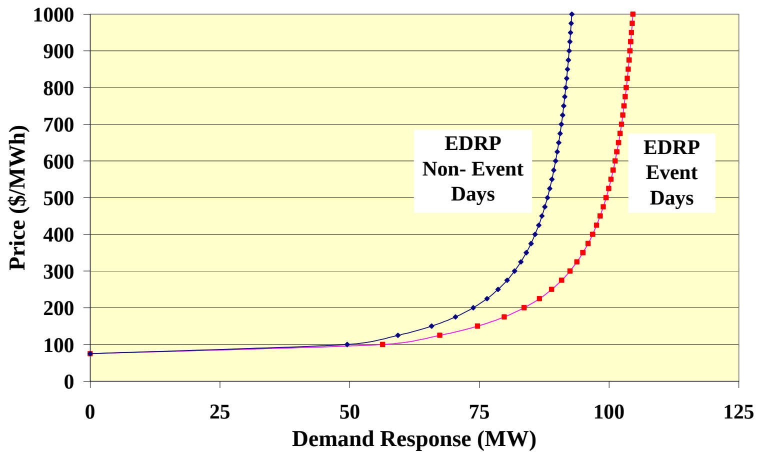
Figure 6-6. Aggregate SC-3A Peak Period DR: Shifting Only and Conservation Adjusted



[137] The elasticities were estimated using 32 customers with complete survey data; elasticity results were matched and extrapolated to the 141 SC-3A accounts with a maximum peak demand of 562 MW.
[138] Customers' peak demand was established individually from their usage during the weekday hours of 7am – 5pm.

Figure 6-7 illustrates the interrelationship between the SC-3A tariff rate and NYISO DR programs. The declaration of an EDRP event day by the NYISO adds an additional 12-15 MW of the estimated curtailments by SC-3A customers that are enrolled in and respond to EDRP.

Figure 6-7. Estimated Impact of EDRP Events on SC-3A Customers' Peak Period Demand Response



6.5 Summary and Conclusions

The merits and impacts of RTP tariffs (and ISO DR programs) have been debated at length in regulatory proceedings and industry forums. The results of the demand-modeling portion of this case study contribute in important ways to the discussion of customers' willingness and capacity to change consumption when they face high marginal prices for electricity as part of their default service.

First, collecting information on customer circumstances and other influences deepened our understanding of the factors that affect SC-3A customers' price responsiveness. We attempted to isolate and accurately portray how customer loads vary systematically with changes in prices, including important customer attributes that are not available from utility customer files. The survey effort produced a wide variety of information, from which we culled the most useful. Given the value of such customer characteristics, it behooves those conducting price response evaluations, whether they are to support a policy action or part of a private business venture, to make provisions to collect similar information.[139] The Final CES model illustrates the potential value and insights that can be obtained from collecting such information.

The second major contribution is the clear demonstration of the wide differences in customers' inclination to respond to prices. While the overall estimate of SC-3A

[139] We believe that it is not feasible to fully identify all factors that cause customers' loads to vary because such an endeavor would require extensive data on the level of each firm's output and prices of its inputs, which few if any firms would be willing to provide.

customers' elasticity of substitution (0.14) is relatively modest, and comports with the findings of other studies of two-part RTP tariffs, our results demonstrate that firm and institution characteristics matter in determining price responsiveness. Thus, if one is concerned with recruiting customers for an RTP tariff (or DR program), the amount of load adjustment in response to price will clearly depend on the type of customers and their choices regarding hedging contracts, their facility and business characteristics (e.g., when their electricity usage peaks), and history of and willingness to invest in enabling technologies. Knowing the differential response capacity of firms assists in identifying which firms to target for participation in such programs.

Third, the Final CES model illustrates the potential value of disaggregated analysis of customer market segments and characteristics, although the relatively small sample and survey response rate creates challenges in extrapolating the results to the SC-3A target population. The 32 customers exhibit a much wider range of elasticity estimates because the models include more detailed information.

Fourth, we attempted to separate and estimate customer response to RTP and ISO DR programs. Government/education customers are the most responsive to SC-3A prices. Industrial customers that participated in EDRP appear to be quite unresponsive to SC-3A prices, but appear to be very responsive to EDRP curtailment incentives. These results suggest that some customers make distinctions: they are not inclined to respond to relative price changes on a routine basis, but for the same reward, do reduce usage when the action is associated with conditions that could lead to forced service outages. While this last result is encouraging, it clearly shows the need for further testing with models that allow the estimated response elasticity of all customers to vary with the size of the peak to off-peak price differential (see Appendix E).

Another priority for additional research is estimating a demand model that allows one to look across days for signs of price responsiveness (see Appendix E). This is also an important way in which customers can respond to price and would provide insight into questions that surround the debate on RTP and ISO DR programs. Some believe that under these types of programs, utilities can suffer revenue losses as customers begin to respond to price signals. However, it is entirely possible that customers will instead reduce load on high priced days but actually make up this lost load on other days. This additional load may cause demand to increase in such a way that utilities may not suffer revenue losses.[140]

[140] Utilities could potentially see their revenue stream rise, particularly if this new demand profile affects customer demand charges. The extra energy consumed during times of shifting load could also generate more revenue for utilities if a customer consumes more to make up for lost production on peak days.

7. Discussion: Implications of NMPC RTP Experience for Policymakers in California (and other states)

7.1 Overview

In this chapter we summarize key findings of our case study of NMPC customers' experience with RTP (i.e., an hourly day-ahead market pricing program). We believe that these results are useful for policymakers in California and other jurisdictions that are considering implementing RTP as the default service tariff for large customers or to achieve demand response goals in a more traditionally regulated market. Forging a sustainable policy on dynamic pricing is often stymied by debates over the design of such rates (e.g., which pricing structure induces the most response or is most cost-effective?). At the heart of this debate is the paucity of empirical information that can be used to characterize and quantify customers' price response under RTP-type pricing. Quantifying the impacts of RTP pricing is important to policymakers, market designers and customers.[141] A primary goal of this study is to contribute to improving the characterization of how customers respond and potentially benefit from participating in RTP service.

Energy regulatory agencies in California are currently focused on developing a range of dynamic pricing pilots and tariffs for customers of all sizes. Utilities are implementing pilot one-part RTP programs for large customers (>200 kW) and two-part RTP tariffs are under development. Utilities are also implementing Critical Peak Pricing (CPP) pilots for residential and small to medium-size commercial customers (CPUC, 2002).[142] The principal policy goal underlying this effort is increasing customer demand responsiveness. However, other objectives – such as improving economic efficiency through use of market-based price signals or providing customers with cost-saving opportunities to reduce peak load and/or shift load to off-peak, less expensive periods – are also important to stakeholders (Jaske and Kaneshiro, 2004).

Because context is extremely important to interpreting results from case studies, we begin this section by comparing the regulatory environment and market circumstances in California with those in which RTP was adopted at NMPC. We then summarize key findings from the NMPC RTP case study and discuss implications for policymakers in California (and other states), focusing on the following issues:

- customer acceptance of and response to RTP (in terms of choices made)
- customer education and information
- tariff design and retail competition
- customer adaptation and coping strategies: hedging price volatility

[141] Customers are keen to better understand the opportunities and consequences associated with RTP pricing. Absent a comprehensive and credible quantification of the benefits and risks of RTP, supplemented by the experiences of others that have been exposed to such pricing, most customers are excusably wary and can be expected to resist RTP.

[142] In this proceeding, stakeholder working groups facilitated by regulatory agency staff are developing tariffs and pilots for large and small customers, which are then ruled upon by the CPUC.

- role of enabling technologies
- the interactions of ISO DR programs and NMPC RTP service
- demand response potential, including both customers' perceived capability and substitution elasticity

7.2 California Market and Regulatory Context for RTP: How is California different from New York?

7.2.1 Market Structure and Context

Over the last 15 years, about 40 utilities have implemented RTP programs. Nearly all of these programs have been implemented initially on a pilot basis by vertically integrated utilities in states where retail competition was not allowed (Barbose et al, 2004). During the last few years, several states and utilities (e.g. New Jersey, Illinois, NMPC, Baltimore Gas & Electric) have considered and/or begun implementing RTP as the default service for large customers as part of a competitive retail market structure.[143]

California's current retail market structure is a product of the consequences of the electricity crisis of 2000-2001. Retail competition was suspended in 2001 in response to the crisis and as a result customers no longer have the option to switch suppliers (CPUC, 2001). However, customers that already had direct access arrangements in place prior to the suspension have been allowed to continue those contracts. While the move to competition has been suspended, California policymakers have made no irreversible decisions about the longer-term structure of retail markets, and are considering several competing proposals or visions.[144]

California's wholesale markets administered by the California ISO (CAISO) are being redesigned and are in transition (FERC, 2002). Currently, the CAISO does not have a functioning day-ahead market to which hourly RTP prices can be indexed and is not planning to implement a day-ahead market until Fall 2005 (Jaske and Kaneshiro, 2004). If RTP is to be implemented before this time, some other acceptable source of hourly price signals must be identified or developed.

In contrast, the introduction of RTP at NMPC went hand in hand with the transition to competitive retail and wholesale markets. Initially, NMPC implemented RTP by estimating day-ahead market prices from system hourly marginal energy costs. This was a transition strategy that allowed NMPC to roll out its tariff along with retail choice. Within a year of the onset of customer choice, the NYISO established a day-ahead energy

[143] In some cases, the intent seems to be to promote price response to improve the efficiency of wholesale and retail electricity markets; in other cases, simply inducing greater switching to competitive suppliers appears to be the desired outcome.

[144] The California legislature is considering bills that return to utility monopoly service or propose core/non-core models in which large customers have the opportunity to procure electric commodity from competitive retailers.

market (DAM) that provided hourly, locational marginal prices and NMPC then indexed its hourly prices to the DAM.

Large customers saw RTP as a vehicle for accessing wholesale market prices and favored indexing to the DAM. NMPC saw the risk-mitigation benefits of allowing customers to purchase in the same markets it was procuring power in, and regulators saw RTP as an efficient rate design and believed that a competitive retail market would provide customers with attractive service offerings. This convergence of interests and beliefs helps explain why RTP for large customers was incorporated into the restructuring settlement and NYPSC Order. At this point, there does not seem to be such a convergence of interest and beliefs in California. Thus, the transitional and unresolved state of California's wholesale and retail power markets shapes several key RTP program design and implementation issues and tempers the applicability of NMPC experience to California.

7.2.2 Regulatory Context

Interest in RTP in California is driven primarily by policymakers' desire to encourage development of price-responsive load that can reduce market prices through more elastic demand and provide load reductions that will help ameliorate tight supply-demand conditions. In New York, policymakers were initially more focused on creating a market structure and tariffs that would stimulate retail competition. After the NYISO day-ahead market experienced price spikes in 2000-01, policymakers became increasingly concerned about the need for price-responsive load. In response, the NYISO developed emergency and economic DR programs and policymakers in New York have developed a renewed interest in RTP for its DR potential.[145]

Issues of concern to various stakeholders in California also differ from the situation at NMPC when default RTP service was adopted.

Mandatory vs. Voluntary RTP. Currently, in California, virtually all stakeholders are opposed to RTP being mandatory or implemented as the default tariff for large customers. Mandatory RTP raises the issue of the appropriateness of placing wholesale market price risk on customers, particularly if alternatives are not available or costly and/or if wholesale prices faced by customers are not derived from a transparent wholesale market. However, designing voluntary RTP programs that are effective and achieve the desired DR policy objectives can also be quite challenging. For example, with a voluntary one-part RTP tariff, customers may self-select – those with load shapes "better" than the class-average (due to consuming disproportionately less peak-period energy) being more likely to enroll. Depending on the program design, some customers may not need to actually alter their loads in response to RTP price signals to save money. This result may be problematic from the standpoint of achieving DR objectives. A two-part RTP tariff resolves the customer bias problem but creates other design challenges:

[145] The NYPSC has been considering the potential for statewide RTP to achieve DR goals in a recent proceeding (NYPSC, 2003).

defining the CBL (the amount of energy the customer otherwise would have consumed) and tying RTP revenues to the rest of the cost-based rate base.

At the time RTP was implemented at NMPC, these issues were not of great concern to large customers because the tariff was not regarded as truly "mandatory", according to our interviews (see Chapter 3). ESCos were expected to provide customers with a variety of hedged alternatives and NMPC also offered a hedged tariff alternative for a transition period (Option 2).

Revenue neutrality. Customer- and class-specific revenue neutrality are important issues to stakeholders in California.[146] In New York, neither of these issues was controversial. Class-level revenue neutrality was not an issue because cost allocation for other rate components (e.g. distribution service) was resolved as part of the restructuring settlement and the entire SC-3A customer class was being migrated to RTP for commodity service. Customer-level revenue neutrality was not of concern because parties expected customers' bills, overall, to go down. Moreover NYPSC staff was convinced that RTP provided a mechanism for allocating costs more efficiently among large customers than traditional ratemaking practices had done.

Cost Effectiveness. Some California stakeholders have raised concerns about the cost-effectiveness of implementing RTP – namely that the costs of program development and marketing, new billing systems, etc., could exceed the expected benefits (e.g., the potential for savings in wholesale market power purchases and possibly resource adequacy requirements). In New York, NMPC's customer billing system was already undergoing significant changes as a result of the restructuring process, and thus incremental costs associated with RTP implementation were viewed as negligible.

7.2.3 Challenges Implementing RTP in California

Implementing RTP in California is challenging given the current market and regulatory environment. First, many industrial/commercial customers in California are dissatisfied with high electric rates and have raised significant concerns regarding current rate design and cost allocation. Representatives of industrial customers argue that they have borne the brunt of rate increases arising from the California energy crisis, far in excess of what could be justified by cost-of-service analysis (Barkovich & Yap, 2003). Because of the cost allocation issues, RTP tariff design is likely to be litigated and may be contentious.

Second, large customers in California are frustrated with the frequent changes in DR program offerings and requirements during the last 3-4 years. Thus, customers are wary

[146] In California, the customer-level revenue neutrality issue has already been largely determined by the CPUC's direction to design two-part RTP tariffs that employ a customer baseline (CBL) to hedge usage at the customer's otherwise applicable TOU tariff rate. Class-level revenue neutrality is more difficult to maintain because of differences in average electric rates (TOU tariffs) and marginal costs (RTP signals); this is exacerbated by the long-term DWR power contracts (WG2, 2002).

and hesitant to commit to new programs, particularly if they must make technology investments to respond effectively.[147]

Third, given the experience during 2000-2001 with volatile and high wholesale prices, customers in California may be reluctant to voluntarily enroll in RTP programs.

Fourth, the lack of transparent, market-based hourly prices that all parties trust presents a challenge. In states where PUCs have mandated RTP as the default service tariff, a pre-condition appears to be the existence of well-established and transparent wholesale markets. Because California does not have an operational day-ahead market, some other source of hourly marginal prices must be utilized if RTP is to be implemented.[148]

7.3 Summary of NMPC RTP Case Study: Key Findings

In this section, we summarize the key findings from our case study of NMPC SC-3A customers that were exposed to RTP.

7.3.1 Customer Acceptance

Customer acceptance, particularly if RTP programs are voluntary, is intimately linked to overall satisfaction with the tariff. Our market research on customer acceptance of RTP at NMPC reveals the following:

- *The sky didn't fall* when RTP was made the default service option in 1998. Survey respondents are relatively satisfied with the SC-3A tariff today, despite the views expressed by some that hedging options and not attractively priced relative to perceived risks (see section 4.2).
- NMPC's pilot RTP programs, which began in the early 1990s, helped create a climate in which customers were comfortable with dynamic pricing tariffs, and ultimately helped pave the way for acceptance of RTP as the default service tariff.
- As of summer 2003, at least 65%of survey respondents were exposed to hourly wholesale prices, either through the default RTP tariff or because they contracted with competitive suppliers for indexed products.
- Customers are less satisfied with the offerings of the competitive retail market, yet they do not blame regulators or the utility for these limitations.
- Because retail market competition has been somewhat disappointing for customers and because wholesale market prices have been higher than expected, industrial

[147] Most RTP pilots in other states have been approved by PUCs for three or more years of operation under stable protocols in order to allow customers to justify investments in enabling technologies and realize the benefits from them.

[148] Parties have suggested using a third-party financial index or allowing the utilities to develop a "synthetic" price based on their cost of procurement. ICE, the Intercontinental Exchange, publishes a power price index, but it does not provide hourly prices (only peak and off-peak averages). Moreover, the utilities no longer calculate system lambdas to estimate their hourly system energy costs and are reluctant to provide such information because of market competitiveness concerns (Jaske and Kaneshiro, 2004).

customer representatives indicated that it would be a "tougher sell" today to mandate RTP as the default service for large customers at NMPC. With the benefit of hindsight, they would have spent more time focusing on the design of other tariff options offered by the utility that hedged price volatility risks (e.g., Option 2).

7.3.2 Customer Education/Information

The move to retail competition and RTP represented a major transition for large customers in New York as they were presented with an array of choices about electricity procurement and supplier choice. In the area of customer education and information, our market research reveals that:

- About 70% of survey respondents rated themselves as relatively unprepared to respond initially to dynamic prices, make the decision to nominate load on Option 2, evaluate strategies to cope with price volatility, or procure electricity from competitive suppliers (see section 4.2.2).
- Customers didn't necessarily expect the utility to provide information on all of these choices and supply options; competitive suppliers, their own trade and industry associations, NYISO, NYPSC, and NYSERDA were also viewed as potential information sources.

7.3.3 Tariff Design and Retail Competition

In New York, the design of the RTP tariff (i.e., unbundling of commodity charges from other rate elements; pass through of day-ahead market prices) and retail market structure were closely linked. Based on our customer market research, we find that:

- NMPC customers are generally satisfied with the unbundled RTP design: 35% offered no suggestions for improvement, although about 15% of survey respondents indicated that they would have preferred a two-part RTP design (see section 4.2.1).
- About 53% of SC-3A customers have taken electric commodity from a competitive supplier at some point in the last five years (see Table 4-1).
- Competitive supply offerings are evolving: initially several ESCos offered attractively priced fixed-rate contracts, while over the last year or two, customers are increasingly taking commodity contracts with prices indexed to the day-ahead market.
- Many NMPC customers indicated in interviews that fixed rate contracts offered by ESCos are not attractively priced at present.

7.3.4 Customer Adaptation and Coping Strategies: Hedging Price Volatility

Under RTP, individual large customers must manage wholesale market price risks that were previously assumed by utilities under TOU tariffs. The appropriateness of transferring this price risk to individual customers is a major issue in RTP implementation. Proponents of RTP point out that risk-averse customers should be able to hedge using a variety of financial products or supply contracts. However, this assumes that customers are fully aware of the risks, are familiar with hedging alternatives, and that such alternatives are readily available to them.

With respect to NMPC SC-3A customers' hedging choices and preferences, our case study reveals the following:

- About 18% of SC-3A customers nominated load under the utility's flat rate alternative to RTP (Option 2) – more probably would have done so if they'd had more information at the time and/or if the contract was less restrictive (e.g., without take-or-pay provisions).
- As of summer 2003, about 35% of survey respondents are hedged in some manner against commodity price risk, predominantly through physical supply contracts with flat or TOU pricing.
- Over the last five years, customers report that hedged supply contracts have become somewhat less common; at the same time there appears to be an increase in the number of financial hedges purchased by customers.
- Many survey respondents report that they want to hedge but that opportunities don't exist or are too expensive.
- Stated preference models based on our conjoint survey suggest that the price premium for hedged products has to be relatively low – otherwise NMPC large customers are more likely to stay on pricing structures that pass through day-ahead market prices (e.g., Option 1 or indexed supply contracts) given the current market environment in New York (see Chapter 5).

Possible explanations for why customers remained on RTP include:

- *Customers are sophisticated* – they monitor day-ahead market prices and adjust usage patterns if necessary. In the face of declining price volatility in NYISO day-ahead markets, higher average DAM prices and unattractive retail market offers, customers make informed decisions not to hedge.
- *Customers are discouraged* – retail market offers are scarce or unattractive;
- *Customers are not fully aware of the price volatility risks* – our interviews provide some evidence for this; for example, some customers said they do not follow prices, rather they only see their bill at the end of the month.
- *Customers have chosen not to choose* – because RTP is the default service, those who have been undecided or not actively sought out alternatives have remained on RTP. Some customers may be more comfortable with taking commodity service from a regulated utility.

In reality, all of these explanations are probably true for at least some customers. Our interviews revealed that customers vary considerably in their attention to electricity usage, knowledge of the range of products and options available to them, and individual management structure and operating conditions.

7.3.5 Role of Enabling Technologies

Customer exposure to high and volatile wholesale market prices, advances in communication, metering, and information technologies, and renewed interest in DR among policymakers has helped stimulate innovations in load management and information and control technologies. These technologies can help customers develop automated DR strategies, monitor load curtailments in near-real time, reduce transaction costs to implement load curtailments, and minimize service or amenity losses. Certain types of energy efficiency investments can also be quite cost-effective in reducing peak demand.

Examining NMPC SC-3A customers' technology investments and their impact on demand response, we find the following:

- About 85% of survey respondents reported making technology investments (mostly energy efficiency-oriented) prior to the introduction of default RTP in 1998. These early investments were driven largely by the perceived need to reduce usage in response to TOU rates that had a lengthy on-peak period (8am-10pm) – thus energy-efficiency investments dominated. Many large customers also developed a conservation ethic, which may explain why many survey respondents indicated foregoing usage in response to high prices or during system emergencies.
- Customer adoption of demand response enabling technologies has increased since 1998, aided in part by financial incentives offered by NYSERDA. About 45% of survey respondents indicated that they had invested in demand response technologies since 1998, with a noticeable shift towards EMCS, peak load management controls, and energy information systems.
- For the sub-set of customers that indicate that they can and do respond to high electricity prices (or ISO system emergencies), most indicated that their DR strategies relied mainly on relatively "low-tech" curtailment solutions (e.g., turning off lights or equipment, asking employees to reduce usage). Our in-depth interviews suggest that many customers are not fully aware of the potential applications and demand reduction potential of DR-enabling technologies they have adopted.

7.3.6 Interactions of ISO DR Programs and RTP Service

In New York, NMPC SC-3A customers were eligible to participate in three DR programs offered by the NYISO. ISO-DR programs complement RTP, providing measurable increases in DR when events are called, particularly for industrial customers.

- We estimate that the overall amount of load curtailed by SC-3A customers increases by about 15% during high price days from those customers that respond to ISO emergency events.
- Industrial DR-program participants are substantially more responsive to ISO program events than to SC-3A prices, while for government/education customers the marginal contribution of ISO DR programs to overall price response is modest.

- About 28% of the study population was enrolled in the NYISO EDRP program, and 9% in the ICAP/SCR program. Enrollment in ICAP/SCR is exclusively by industrial customers; EDRP is particularly popular among government/educational institutions.
- Based on our customer interviews and other studies (Neenan et al, 2003), NYISO "emergency" DR programs are attractive to customers because:
  - they provide significant financial rewards (e.g. $500/MWh floor price and/or monthly reservation payments)
  - they allow customers to assist in "keeping the lights on" – there is a sense among customers that reliability is a public concern and that it is their corporate responsibility to participate ("good citizen" factor),
  - the NYISO calls events, so customers don't need to monitor hourly commodity prices, and
  - participation and/or response may be voluntary, which is important for many customers.

7.3.7 Demand Response Potential

A major focus of this study was to assess the price responsiveness of SC-3A customers. We did this qualitatively through survey questions that probed customers' perceived response capability, and quantitatively through the estimation of price elasticity using demand models.

- About 54% of SC-3A survey respondents claimed they were unable to curtail at all, 31% said they could curtail by forgoing usage only, and 15% said they could shift (or shift and forgo) usage;
- Extrapolating from the modeling results, aggregate demand response that could be expected from 141 SC-3A customers at a price of $0.50/kWh is ~100 MW, about 18% of these customers' maximum demand.
- While many of the NMPC SC-3A customers are not highly price-responsive, roughly one-third (10 of 32) of our Final CES model sample have an elasticity of substitution greater than 0.20. These highly elastic customers are distributed across the three main business sectors (Industrial, Commercial, Government and Education). Electricity intensive customers are less price-responsive on average as are customers who peak in the afternoon hours. Investments in energy management tools, in and of themselves, do not necessarily assist customers to be more price-responsive, but it does provide them with information to make better overall energy usage decisions.

7.4 Implications for Policymakers in California (and Other States)

In this section, we discuss the implications of our case study of customer experience with RTP at NMPC for policymakers in California and other states.

7.4.1 Retail Market Structure and RTP Tariff Design

- There is a fundamental policy trade-off between the "sink or swim" approach, in which a competitive retail market is facilitated by mandating RTP as the default tariff (e.g., the NMPC model), and a “voluntary” approach, in which the utility offers RTP in addition to fixed rate tariffs and/or financial hedging products.

- The voluntary approach protects customers if there is a paucity of hedging options, but ironically is likely to slow the rate of development of physical and financial hedging products.
- In California, until wholesale (and retail) market structure issues are fully resolved and transparent prices are routine, the voluntary RTP participation approach may be more appropriate.
- Based on the NMPC experience, should California policymakers decide to restore and encourage retail competition for large customers, making RTP the default service tariff for those customers appears to be consistent with this goal.
    - Our case study of NMPC RTP experience suggests that large customers can adapt to RTP under such conditions. However policymakers in California should determine whether retail markets are likely to provide customers with sufficient options to hedge initially, either through commodity or financial contracts offered by competitive retailers.
    - Even in well-established wholesale electricity markets, large customers may be disappointed with the pricing premiums and choices of hedging contracts offered by retailers. Thus, if hedging options are deemed to be deficient to meet customer needs, a NMPC Option 2 type hedge may be warranted, at least initially to prime the pump.
- In a retail market structure that encourages direct access or a “hybrid” retail market structure such as currently exists in California (where some customers have grandfathered rights to direct access), designing a hedged service offered by utilities in addition to RTP raises a number of difficult policy issues:
    - Is it appropriate for regulated utilities to offer financial hedging products to customers, like Georgia Power does? If so, how is a fair, revenue neutral hedge computed? Who underwrites such hedges, utility shareholders or other ratepayers?
    - Should such hedged tariffs be available only during a defined transition period or indefinitely?
    - If part of a transition strategy, then what criteria should be used for sunset provisions of a hedged tariff? A fixed time period? Evidence of robust retail market?
- If RTP is rolled out before retail market structure questions are resolved, or during a transition period, then a two-part RTP design may be the most practical way to introduce customers to dynamic pricing. Two-part RTP tariffs are potentially attractive options for customers as the CBL effectively hedges most of their exposure to price volatility. However, two-part RTP tariffs raise a number of program design and policy issues that must be addressed:
    - Is two-part RTP a desirable equilibrium result for large customers, or is it better used as a transition vehicle?
    - If the implicit benefits to customers are not sufficient to achieve the desired level of participation (and/or demand response), what additional inducements are justified and effective?

- What constitutes enough participation? How would such goals be set, and who would be responsible for achieving them? What inducements, such as cost recovery, are appropriate for regulated utilities? Should independent RTP service providers be authorized to recruit customers in anticipation of sharing benefits with customers, as is prominent in ISO DR programs?
- Are there implications for utilities' revenue requirements and allocation over time as RTP participants' customers adjust usage to prices?
- What constitutes the base rate to which the RTP tariff is made revenue neutral? Is that base rate adjusted over time to reflect changes in other rates, and if so how?
- What rules should be promulgated for determining the CBL? Can the CBL be set once and for all without undesirable repercussions in later years? If not, how should it be adjusted over time?

7.4.2 Implementation of RTP Tariffs and Customer Acceptance

- In California, large customers have expressed concerns about high electric rates and price volatility, having witnessed extreme wholesale market price spikes during the crisis of 2000-2001. Thus, large customer representatives in California seem to be more skeptical that RTP tariffs will suit their needs than were their counterparts in New York when NMPC RTP offering was first introduced in 1998. These concerns must be made explicit and addressed in order to assure program success.
- An important lesson from the NMPC experience is that customers are diverse, and therefore a range of inducements is needed to coax out the available price response. California and other states should consider establishing an overall strategy to facilitate DR through a combination of pilot RTP programs, staged RTP implementation, and utility or ISO DR programs. This approach provides customers with a "training ground" to gain experience and response capability and offer feedback.
- It is critical to develop an education, marketing and information strategy that complements the roll-out of RTP tariffs and includes information about the range of service, hedging and supply options available (assuming retail access is revived). Utilities, regulatory agencies, and other market participants will need to undertake substantial efforts to educate, inform and train customers on their tariff and supply choices and potential response strategies. It is equally important to offer customers ongoing technical assistance to help assess their load curtailment capabilities and develop control strategies, particularly if demand response is a major rationale for implementing RTP.

7.4.3 Customer Coping and Response Strategies: Hedging Products

Our research shows that many NMPC customers are concerned about wholesale market price volatility and want access to products that hedge this risk. At the same time, products available in the retail market do not necessarily meet customer needs, either in terms of the types of products available or the embodied risk premium. Policymakers in California and other states should consider the following questions:

- What range of hedging choices is required to induce large customers to accept RTP-type pricing services? Should customers have access to unlimited-quantity hedged supply options or take-or-pay type contracts?
- If retailers do not provide the range of hedging products envisioned, is it because such products are truly uneconomical for competitive retailers to offer, or because market barriers or imperfections stand in the way?
- If the former, should utilities or other entities be responsible for offering such products? If the latter, what policy interventions could address these market obstacles?
- If the retail market is to be relied upon to provide hedged alternatives to RTP, it should not be assumed that all customers are fully aware of all the options available to them. Financial hedging products, for example, may be less well known to or understood by customers than hedged commodity supply options. Thus, policymakers should develop strategies to ensure that customers are well educated about their hedging options.

7.4.4 Customer Coping and Response Strategies: Role of Enabling Technologies

- Load management, energy information and control systems can facilitate load response, but because the benefits are uncertain, financial incentives and technical support may be necessary to encourage customer investment. This support may be required over an extended period because these technologies are relatively new and will likely continue to evolve and improve as their market penetration increases.
- In designing DR programs that provide financial incentives to customers, administrators of public benefit funds should tie incentives for DR technologies to enrollment or participation in dynamic pricing tariffs or utility/ISO DR programs.[149]

7.4.5 Interactions between RTP and Demand Response Programs

- Our case study of NMPC customers underscores the notion that ISO-based emergency DR programs can complement RTP by providing the means for adjusting prices on short notice when power system conditions diverge radically from those that determined the day-ahead prices.
- In New York, DR programs are well coordinated and harmonized among the ISO, utilities, and state agencies.[150] An important result is that there is a common voice regarding the state of the market and the value of demand response that underwrites and authenticates program participation by otherwise skeptical customers.

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[149] Ideally, financial incentives to customers should be tied in some fashion to performance in DR programs, but this is quite difficult given the fact that "emergency" DR programs may be rarely called, or Critical Peak Pricing programs may not have triggering price events. As a substitute, ISO or public benefits program administrators often require periodic testing to ensure that DR capability is still available at facilities.

[150] The NYISO DR programs provide an overall framework for utilities and other LSE to market programs to customers. NYSERDA also offers several peak demand reduction programs that provide technical assistance and incentives to customers and load aggregators in order to overcome perceived market barriers. This DR program "infrastructure" helps train customers to become more price-responsive.

7.4.6 Demand Response Potential of RTP

- The NMPC experience suggests that price response to RTP is modest overall among larger customers. A tripling or quadrupling of short-term hourly prices is likely to induce a 10-15% reduction in usage.
- Price response in an RTP-type program varies substantially among individual customers. A few very responsive customers account for much of the overall response. Many customers appear to be very inelastic, and therefore subject to the adverse affects of high price volatility.
- A surprising finding, at least given the conventional wisdom, is that education and government facilities typically exhibited the greatest price response among NMPC SC-3A customers.
- Customers undertake a variety of actions in response to price changes. Some reschedule activities, some forego consumption, and some accomplish both. These differences are important as they affect the level of the customer's bill savings, the utility or provider revenue impacts, and the impact on system load. These have implications for how participation is marketed, the value of enabling technologies, and the likely persistence of the response in periods of extended high prices.

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Customer Response to Day-ahead Wholesale Market Electricity Prices: Case Study of RTP Program Experience in New York

Appendix

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Disclaimer

Appendix A: Regulator and Stakeholder Interview Protocol

Lawrence Berkeley National Laboratory and Neenan Associates (LBNL's sub-contractor) have received funding from the California Energy Commission (CEC) to conduct a case study of Niagara Mohawk's real time pricing program that assesses customer response to tariffs based on day-ahead wholesale market prices (i.e., RTP) in a retail competition environment.

The CEC (and CPUC) are interested in the regulatory and policy experience in New York, as these agencies are currently examining issues in developing dynamic pricing tariffs for California and are analyzing the merits of alternative strategies (e.g., "real-time pricing" tariffs, price-responsive load bidding programs administered by ISOs) that seek to increase customer participation in electricity markets.

As part of this research, we are conducting interviews about the regulatory proceeding that led to the adoption of Niagara Mohawk's SC-3A Option 1 electricity tariff in 1998 and customer experiences with "real-time" pricing tariffs during the last four years. As a key actor in this proceeding, your insights into the process, major policy and program design issues, lessons learned and suggestions for other policymakers and regulators are of great interest to policymakers in California.

Introduction/ Overview

1. Please provide the following information about yourself:

   a. Name:
   b. Organization:
   c. Title:
   d. Address:
   e. Phone:
   f. Fax:
   g. E-mail:

2. Please describe your role in the regulatory proceedings (Cases 94-E-0098 and 96-E-0134) that led to the adoption of the NMPC SC-3A Option 1 tariff in 1998.

3. In your opinion, what were the most important regulatory/policy issues pertaining to this tariff?

Process/ Goals

4. What were the NYPSC's overarching policy goals? How did NMPC's proposed Option 1 tariff support those goals?

5.a. Describe the regulatory process and the approach used to implement the tariff (e.g., contested rate case, settlement, rulemaking/workshop).

  b. How long did the process take?

6. How receptive was NMPC to the idea of RTP? What were the major issues over which it was concerned? If so, how were they resolved?

7. Were similar proceedings attempted in other utility service territories in New York? If so, what factors account for their lack of implementation?

Competing Proposals & Tariff Design Issues

8. NMPC already had a pilot RTP program in place that employed a 2-part tariff with customer baseline loads (CBL). Why was a different, 1-part (market-based) tariff design proposed instead?

9. What was the rationale for the decision to bill T&D charges as a demand charge (per kW), rather than a volumetric (per kWh) charge?

10. Aside from the tariff that was actually implemented, were there competing proposals? If yes, please describe them. Who was responsible for offering them?

Ultimately, RTP was offered as the default electricity service to large commercial/ industrial customers under Option 1. In addition, an alternative fixed-price time-of-use tariff was offered under a five-year contractual agreement as Option 2.

11. Was there strong debate over the legality or appropriateness of providing a RTP tariff as the default service? If so, how was this issue resolved?

12. How and why was the decision to offer Option 2 made? How/why was the 5 year contract length arrived at? What options will customers on this tariff have when the contracts expire next year?

13. How were the alternative fixed-price tariff electricity supply service rates (per kWh) arrived at? Was there controversy over the appropriate risk premium to include? If yes, how was this issue resolved?

14. What criteria were used by the NYPSC in their decision to adopt this tariff structure? Did customer ease of understanding constitute a major criteria for evaluating potential tariff designs?

15. How much weight did the following equity concerns have in the decision to adopt the RTP tariff vs. other options?

    a. *ability of program to provide net system benefits (e.g., net cost reductions)*
    b. *revenue neutrality by customer class*
    c. *revenue neutrality by customer*
    d. *non-discrimination by size or end-use*
    e. *minimization of gaming opportunities*

16. Please rate the importance of the following issues in the regulatory proceeding (1= LEAST IMPORTANT, 5=MOST IMPORTANT).

Potential Issue	Importance
voluntary vs. mandatory tariff	
utility risk exposure	
revenue neutrality (utility perspective)	
one-part vs. two-part tariff	
establishing customer baseline load (CBL)	
transmission & distribution (T&D) utility cost recovery	
customer acceptance	
customer equity concerns	
customer risk exposure	
offering ways to limit customer risk	
overall system benefits (e.g., lowered costs, grid reliability)	
level/reliability of demand response potential	
program costs	

<u>Tariff Implementation Costs</u>

17. How significant a factor was cost in deciding on the RTP tariff vs. other options?

18. Were there significant incremental costs involved in adopting the RTP tariff (e.g., infrastructure costs, O&M and financing carrying costs, marketing and education costs, customer costs, scalability of infrastructure)?

19. Were there cost-effectiveness issues? Was a cost/benefit analysis performed?

Relative Importance of SC-3A Option 1 Tariff and Demand Response Programs

20. In your opinion, what is the relationship between RTP and other demand response programs? What are the strengths and weaknesses of the different approaches?

21. Please compare the relative effectiveness of the Option 1 tariff to the Day Ahead Demand Response Program (DADRP) in delivering the benefits described below (1=RELATIVELY INEFFECTIVE, 5=EXTREMELY EFFECTIVE):

Demand Response Benefit	Option 1 tariff	DADRP
size of demand response (MW)		
focus of response when and where needed		
year-round availability		
encouragement of peak-load reduction		
encouragement of load shifting		
encouragement of off-peak load building		
potential for system benefits from response (e.g., decreased grid congestion, lowered costs)		
sustained potential for participation		

RTP Tariff Results

22. What was the expected level of demand response (MW) from the RTP tariff? In your opinion, has this materialized?

23. What level of participation (number of customers) was expected from the RTP tariff vs. the alternative fixed-rate tariff offered? Did the high (~80%) subscription rate come as a surprise?

Summary

24. In your opinion, has the NMPC large customer RTP tariff been successful at accomplishing the goals it was meant to address? Why or why not?

25. What, in your opinion, were the most significant barrier(s) to overcome in the regulatory process? What factor(s) were most conducive to its success?

26. If the process could be repeated from scratch, what would you recommend be done differently? What would you leave unchanged?

Appendix B: Customer Survey

1. Please verify the following contact information we have for you so that upon completing this survey, we may properly enter you into the prize drawing.

1.Name: ____

2.Organization: ____

3.Address: ____

____

4.Phone: _____________________ *5.Fax:* _____________________

6.E-mail: _____________________

We are going to ask you a series of questions concerning your business and the ways in which you respond and adapt to changes in electricity prices. Please answer specifically for the location you have just given us, even if you have other facilities or locations in the state or around the country

2. What is your position/title in the organization?

- ❑ 1. FACILITY MANAGER
- ❑ 2. ENERGY MANAGER
- ❑ 3. PURCHASING/PROCUREMENT MANAGER
- ❑ 4. GENERAL MANAGER
- ❑ 5. CEO/CFO
- ❑ 6. VP OF ________________________________
- ❑ 7. OTHER (PLEASE SPECIFY)____________________________________

3. What is the major business or institutional activity of your facility? (CHECK ONLY ONE)

- ❑ 1. HEAVY MANUFACTURING
- ❑ 2. LIGHT MANUFACTURING
- ❑ 3. WHOLESALE TRADE
- ❑ 4. RETAIL TRADE
- ❑ 5. GOVERNMENT
- ❑ 6. EDUCATION – RESEARCH
- ❑ 7. EDUCATION - GENERAL

- ❑ 8. HEALTH SERVICES
- ❑ 9. LODGING
- ❑ 10. AGRICULTURE
- ❑ 11. COMMERCIAL-OFFICE
- ❑ 12. COMMERCIAL-RETAIL
- ❑ 13. APARTMENT/CO-OP/CONDOMINIUM BUILDING
- ❑ 14. OTHER (PLEASE SPECIFY) ____

4. On average, what percent of your facility's total annual operating cost does your electricity bill represent?

- ❑ 1. LESS THAN 1%
- ❑ 2. BETWEEN 1% AND 3%
- ❑ 3. BETWEEN 4% AND 6%
- ❑ 4. BETWEEN 7% AND 10%
- ❑ 5. BETWEEN 11% AND 20%
- ❑ 6. GREATER THAN 20%
- ❑ 7. DON'T KNOW

5. How has this electricity component of your facility's total annual operating cost changed over the past 5 years?

- ❑ 1. INCREASED
- ❑ 2. DECREASED
- ❑ 3. NOT CHANGED AT ALL **(GOTO QUESTION 7)**
- ❑ 4. DON'T KNOW **(GOTO QUESTION 7)**

6. In what year did the largest change in the electricity component of your facility's total annual operating cost occur?

- ❑ 1. 1999
- ❑ 2. 2000
- ❑ 3. 2001
- ❑ 4. 2002
- ❑ 5. 2003
- ❑ 6. DON'T KNOW

7. Please rank the following time periods according to your facility's usage of electricity from highest to lowest use on a "normal-use" weekday (1=HIGHEST USE PERIOD, 4=LEAST USE PERIOD):

RANK	TIME PERIODS
_____	1. 8:00 A.M. – 11:59 A.M.
_____	2. 12 NOON – 4:59 P.M.
_____	3. 5:00 P.M. – 9:59 P.M.
_____	4. 10:00 P.M. – 7:59 A.M.

8. Does your facility's electricity usage fluctuate due to changes in temperature during the summer?

❑ 1. YES **(GOTO QUESTION 9)**
❑ 2. NO **(GOTO QUESTION 10)**

9. By how much does your facility's electricity usage fluctuate on very hot days in comparison to days with average temperatures during the summer?

❑ 1. LESS THAN 2%
❑ 2. BETWEEN 3% AND 6%
❑ 3. BETWEEN 7% AND 10%
❑ 4. MORE THAN 10%
❑ 5. DON'T KNOW

10. Over a 24-hour period, how many production shifts does your facility operate on a weekday?

❑ 1. ONE
❑ 2. TWO
❑ 3. THREE
❑ 4. MORE THAN THREE

11. Is a large portion of your electricity load comprised of batch production processes?

❑ 1. YES
❑ 2. NO
❑ 3. DOES NOT APPLY
❑ 4. DON'T KNOW

12. Over the past 5 years, which of the following months typically constitute those where a higher than average level of electricity is consumed due to increased business activity? (CHECK ALL THAT APPLY)

❑ 1. JANUARY

- ❑ 2. FEBRUARY
- ❑ 3. MARCH
- ❑ 4. APRIL
- ❑ 5. MAY
- ❑ 6. JUNE
- ❑ 7. JULY
- ❑ 8. AUGUST
- ❑ 9. SEPTEMBER
- ❑ 10. OCTOBER
- ❑ 11. NOVEMBER
- ❑ 12. DECEMBER
- ❑ 13. NONE

13. Over the past 5 years, which of the following weekdays typically constitute those where a higher than average level of electricity is consumed due to increased business activity? (CHECK ALL THAT APPLY)

- ❑ 1. MONDAY
- ❑ 2. TUESDAY
- ❑ 3. WEDNESDAY
- ❑ 4. THURSDAY
- ❑ 5. FRIDAY
- ❑ 6. NONE

The next section contains a series of questions concerning your participation in and opinions of Niagara Mohawk's SC-3A tariff rate that was re-designed and implemented back in November of 1998. This re-designed SC-3A rate will hereafter be referred to as SC-3A Retail Choice. Even if your facility chose the fixed-rate option, otherwise known as Option 2 in the tariff, which was only offered once, your answers to these questions are still very valuable to us.

14. Did your facility have any experience with the following time-varying rate structures before 1998? (CHECK ALL THAT APPLY)

- ❑ 1. HOURLY INTEGRATED PRICING PILOT (HIPP)
- ❑ 2. VOLUNTARY INTERRUPTIPLE PILOT PROGRAM (VIPP)
- ❑ 3. INTERRUPTIBLE RIDER (SC-3B OR SC-3C)
- ❑ 4. NONE OF THE ABOVE
- ❑ 5. DON'T KNOW

15. In general, how satisfied is your facility with the way Niagara Mohawk re-designed its SC-3A tariff rate in 1998?

COMPLETELY DISSATISFIED **1 2 3 4 5** COMPLETELY SATISIFIED

16. What is the primary issue that could haven been improved in the design of this rate offering? (CHOOSE ONLY ONE)

- ❑ 1. FIXED-RATE OPTION SHOULD NOT HAVE BEEN A "TAKE-OR-PAY" CONTRACT
- ❑ 2. FIXED-RATE OPTION SHOULD HAVE ALLOWED FOR A PROPORTION OF DEMAND TO BE NOMINATED NOT A FIXED MW VALUE
- ❑ 3. MORE INFORMATION SHOULD HAVE BEEN PROVIDED UP FRONT TO ASSIST MY FIRM IN MAKING A BETTER, MORE INFORMED DECISION
- ❑ 4. TOU-STYLE DEMAND CHARGE SHOULD BE REMOVED
- ❑ 5. THE VARIABLE RATE OPTION SHOULD HAVE COVERED ONLY CHANGES IN ELECTRICITY USAGE RELATIVE TO A BASELINE LEVEL OF LOAD
- ❑ 6. OTHER (PLEASE EXPLAIN) ________________________________
- ❑ 7. NONE

17. Just prior to beginning service on SC-3A Retail Choice, how well prepared was your facility to make the choice to nominate load for Option 2?

NOT AT ALL PREPARED **1 2 3 4 5** COMPLETELY PREPARED

18. Just prior to beginning service on SC-3A Retail Choice, how much information was your facility given by utilities, state agencies, retail suppliers or others concerning forecasted energy prices for the period of 1998 - 2003?

NO INFORMATION **1 2 3 4 5** COMPLETE INFORMATION

19. Just prior to beginning service on SC-3A Retail Choice, how familiar was your facility with commodity hedging methods and products?

NOT AT ALL FAMILIAR **1 2 3 4 5** COMPLETELY FAMILIAR

20. Just prior to beginning service on SC-3A Retail Choice, how much information was your facility given by utilities, state agencies, retail suppliers or others concerning opportunities for procuring hedging arrangements from an entity other than Niagara Mohawk in order to reduce your price-risk exposure?

NO INFORMATION **1 2 3 4 5** COMPLETE INFORMATION

21. Just prior to beginning service on SC-3A Retail Choice, how much experience did your facility have shopping for alternative electric commodity suppliers?

TOTALLY INEXPERIENCED **1 2 3 4 5** TOTALLY EXPERIENCED

22. Just prior to beginning service on SC-3A Retail Choice, how much information was your facility given by utilities, state agencies, retail suppliers or others concerning opportunities for procuring your electric commodity from an entity other than Niagara Mohawk?

NO INFORMATION **1 2 3 4 5** COMPLETE INFORMATION

23. Which of the following best characterizes your facility's current curtailment capability?

- ❑ 1. SHIFT ELECTRICITY USAGE FROM ONE TIME PERIOD TO ANOTHER **(GOTO QUESTION 25)**
- ❑ 2. FOREGO ELECTRICITY USAGE DURING A TIME PERIOD **(GOTO QUESTION 25)**
- ❑ 3. BOTH SHIFT AND FOREGO ELECTRICITY USAGE **(GOTO QUESTION 24)**
- ❑ 4. UNABLE TO CURTAIL LOAD **(GOTO QUESTION 31)**

24. According to your current curtailment capability, what percentage of your facility's expected reduction in electricity usage would be allocated to actions that shift this usage from one time period to another versus actions that forego the usage entirely? (THE PERCENTAGES SHOULD ADD TO 100)

% SHIFT: ___________________

% FOREGO: ___________________

25. Which of the following list of actions did your facility undertake to reduce electricity usage in response to high prices over the past 5 years? (CHECK ALL THAT APPLY)

- ❑ 1. NO ACTION WAS UNDERTAKEN
- ❑ 2. STARTED ONSITE OR EMERGENCY/BACKUP GENERATION
- ❑ 3. ASKED EMPLOYEES OR BUILDING OCCUPANTS TO REDUCE ELECTRICITY USE
- ❑ 4. TURNED OFF OR DIM LIGHTS
- ❑ 5. REDUCED OR HALTED USE OF AIR CONDITIONING
- ❑ 6. REDUCED OR HALTED USE OF REFRIGERATION
- ❑ 7. REDUCED OR HALTED USE OF WATER HEATING
- ❑ 8. REDUCED PLUG (OFFICE EQUIPMENT) LOADS
- ❑ 9. TURNED OFF OR LIMITED USE OF ELEVATORS AND/OR ESCALATORS
- ❑ 10. SHUT DOWN PLANT(S) OR BUILDING(S)
- ❑ 11. COMPLETELY HALTED MAJOR PRODUCTION PROCESSES

- ❑ 12. ALTERED MAJOR PRODUCTION PROCESSES
- ❑ 13. SHUT DOWN EQUIPMENT
- ❑ 14. OTHERS (PLEASE EXPLAIN)

____

26. If you indicated that your facility used on-site generation to reduce electricity usage during high priced periods, please estimate the amount of electricity demand, in MWs, this unit(s) would produce.

________________ MW

27. During the weekday hours of 11 A.M. to 5 P.M., what must the average price for electricity have to be for your facility to begin reducing its electricity usage?

_____________ $/MWh

28. When this indicated price is observed during the weekday hours of 11 A.M. to 5 P.M., on average how much of your electricity demand, both in average MWs and as a percent of your facility's electricity usage at the time, do you generally reduce?

_____________ MW

_____________ % OF ELECTRICITY USAGE AT THE TIME

29. During the weekday hours of 11 A.M to 5 P.M. when prices reach the level that you reduce and curtail electricity usage, how long does it take for your facility to resume full operation?

______________ HOURS

30. Assume the average hourly price to purchase electricity on a weekday from 11 A.M. to 5 P.M. is $1000/MWh, how much of your facilities demand, in average MWs, would your facility expect to reduce?

_____________ MW

31. Which of the following technologies did your facility have in place before Niagara Mohawk implemented SC-3A Retail Choice in November of 1998? (CHECK ALL THAT APPLY)

- ❑ 1. PROCESS/BUILDING AUTOMATION SYSTEMS
- ❑ 2. REAL-TIME ACCESS TO INTERVAL ELECTRICITY METER DATA
- ❑ 3. ENERGY INFORMATION SYSTEMS
- ❑ 4. CONTROL DEVICES ON SPECIFIC PROCESSES OR USES

- ❑ 5. PEAK-LOAD MANAGEMENT CONTROL DEVICES
- ❑ 6. ENERGY EFFICIENT LIGHTING
- ❑ 7. ENERGY EFFICIENT HVAC SYSTEMS OR EQUIPMENT
- ❑ 8. ENERGY EFFICIENT MOTORS, PUMPS, VFDs
- ❑ 9. NONE
- ❑ 10. DON'T KNOW

32. Since beginning service on SC-3A Retail Choice, did your facility make any additional investments in energy management and/or information systems that would help you respond better to hourly changes in price?

- ❑ 1. YES **(GOTO QUESTION 33)**
- ❑ 2. NO **(GOTO QUESTION 35)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 35)**

33. Since beginning service on SC-3A Retail Choice, in which of the following technologies did your facility invest? (CHECK ALL THAT APPLY)

- ❑ 1. PROCESS CONTROLS AND/OR AUTOMATION SYSTEMS
- ❑ 2. NEAR REAL-TIME ACCESS TO INTERVAL ELECTRICITY METER DATA (E.G. NMPC'S ENERGY CHECK ONLINE)
- ❑ 3. ENERGY INFORMATION SYSTEM
- ❑ 4. ENERGY MANAGEMENT CONTROL SYSTEM
- ❑ 5. DIRECT LOAD CONTROL DEVICES
- ❑ 6. PEAK-LOAD MANAGEMENT OR CONTROL DEVICES
- ❑ 7. ENERGY EFFICIENT LIGHTING
- ❑ 8. ENERGY EFFICIENT HVAC SYSTEMS
- ❑ 9. ENERGY EFFICIENT MOTORS AND/OR PUMPS

34. In which year did your facility first utilize most of these technologies or equipment to better respond to hourly changes in price?

- ❑ 1. 1999
- ❑ 2. 2000
- ❑ 3. 2001
- ❑ 4. 2002
- ❑ 5. 2003
- ❑ 6. DON'T KNOW

Electricity consumers in New York State are allowed to choose who supplies their electricity commodity. Next, we are going to ask you a series of questions concerning your interactions with these competitive electricity suppliers.

35. Did your facility nominate any of its peak demand under SC-3A's Retail Choice fixed-price electricity rate option, known as Option 2?

- ❑ 1. YES (**GOTO QUESTION 36)**
- ❑ 2. NO **(GOTO QUESTION 37)**

36. How satisfied is your facility with its decision to be served under the fixed-price electricity rate option (a.k.a. Option 2)?

COMPLETELY DISSATISFIED **1 2 3 4 5** COMPLETELY SATISIFIED

37. Hypothetically, if your facility were able to nominate a portion of your demand for an identically designed fixed-price electricity rate option that was provided by a competitive electricity supplier for the next five (5) years, how many MWs, on average, would you elect to have served for the summer on-peak and off-peak periods and the winter on-peak and off-peak periods?

SUMMER ON-PEAK ___________ SUMMER OFF-PEAK ________________

WINTER ON-PEAK ___________ WINTER OFF-PEAK ________________

38. At any time since November 1998, when SC-3A Retail Choice was first introduced, did your facility take service under any competitively offered rate options?

- ❑ 1. YES **(GOTO QUESTION 39)**
- ❑ 2. NO **(GOTO QUESTION 42)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 42)**

39. We would like to get a general sense of your facility's electric commodity rate and/or contract history since November 1998, when SC-3A Retail Choice was introduced. For each time period listed in the table below, please indicate which types of electric commodity rates or contracts most closely represent the ones your facility was on by checking the appropriate boxes. The summer months correspond to May, June, July, August and September, while the winter months represent October through December of the same year and then January through April of the following year.

Time Period	Flat Rate	Time-Of-Use Rate	Price Index	Volumetric Collar	Other	SC-3A
Winter 1998 - 1999						
Summer 1999						
Winter 1999 - 2000						
Summer 2000						
Winter 2000 - 2001						
Summer 2001						
Winter 2001 – 2002						
Summer 2002						
Winter 2002 – 2003						
Summer 2003						

40. What were the reasons your facility chose to take service under a competitively offered rate option? (CHECK ALL THAT APPLY)

- ❑ 1. SC3-A PRICES EXPECTED TO BE TOO VOLATILE
- ❑ 2. NO LONGER INTERESTED IN RATE WHERE PRICES VARIED EACH HOUR
- ❑ 3. FOUND WE WERE UNABLE TO ADJUST LOAD IN RESPONSE TO VARYING PRICES
- ❑ 4. RECEIVED FINANCIALLY ATTRACTIVE OFFER FROM A COMPETITIVE SUPPLIER
- ❑ 5. DISCOVERED THAT ADJUSTING LOAD IN RESPONSE TO VARYING PRICES WAS NOT COST-EFFECTIVE
- ❑ 6. WANTED MORE PREDICTABLE RATE STRUCTURE
- ❑ 7. THE TERMS OF OPTION 2 WERE UNACCEPTABLE
- ❑ 8. WISHED TO TAKE ADVANTAGE OF CUSTOMER SERVICE BACK-OUT CREDIT
- ❑ 9. OTHER (PLEASE EXPLAIN) ____

41. We would also like to get a general sense of your facility's history with financial hedge products since SC-3A Retail Choice was introduced in November 1998. For each time period listed in the table below, please indicate which types of hedge products most closely represent the ones your facility had purchased by checking the appropriate boxes. The summer months correspond to May, June, July, August and September, while the winter months represent October through December of the same year and then January through April of the following year.

Time Period	Price Collar	Price Cap	Financial Swap	Other	None
Winter 1998 - 1999					
Summer 1999					
Winter 1999 - 2000					
Summer 2000					
Winter 2000 - 2001					
Summer 2001					
Winter 2001 – 2002					
Summer 2002					
Winter 2002 – 2003					
Summer 2003					

We would now like to ask you some questions concerning the demand response programs currently offered in New York State.

42. Has your facility ever registered for the Emergency Demand Response Program, commonly referred to as EDRP?

- ❑ 1. YES **(GOTO QUESTION 43)**
- ❑ 2. NO **(GOTO QUESTION 45)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 45)**

43. In which years did your facility reduce load in response to a declared EDRP event? (CHECK ALL THAT APPLY)

- ❑ 1. 2001
- ❑ 2. 2002
- ❑ 3. 2003

44. Assume the hourly price to purchase electricity from 11 A.M. to 5 P.M. were $500/MWh and an EDRP event was declared during this time period paying you an additional $500/MWh, on average how much of your demand, in MWs, would your facility expect to reduce?

______________________ MWs

45. Has your facility ever registered for the Day-Ahead Demand Response Program, commonly referred to as DADRP?

- ❑ 1. YES **(GOTO QUESTION 46)**
- ❑ 2. NO **(GOTO QUESTION 47)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 47)**

46. In which years did your facility submit a bid to curtail to the DADRP? (CHECK ALL THAT APPLY)

- ❑ 1. 2001
- ❑ 2. 2002
- ❑ 3. 2003
- ❑ 4. NONE

SKIP TO QUESTION 48

47. Which one of the following best describes the primary reason your facility chose to not register for the DADRP?

- ❑ 1. POTENTIAL BENEFITS DON'T JUSTIFY THE RISKS
- ❑ 2. PENALTY IS TOO SEVERE
- ❑ 3. PAYMENTS ARE TOO LOW
- ❑ 4. UNABLE TO SHIFT USAGE
- ❑ 5. INADEQUATE KNOWLEDGE OF DADRP REQUIREMENTS
- ❑ 6. INABILITY TO USE DIESEL GENERATORS
- ❑ 7. OTHER ___________________________

❑ 8. DON'T KNOW

48. How comfortable are you with creating a load curtailment plan to meet a specific MW reduction target?

NOT COMFORTABLE **1 2 3 4 5** VERY COMFORTABLE

49. How comfortable are you with monitoring the NYISO's Day-Ahead market electricity prices to determine whether and if to bid?

NOT COMFORTABLE **1 2 3 4 5** VERY COMFORTABLE

50. How comfortable are you with determining at what price to bid?

NOT COMFORTABLE **1 2 3 4 5** VERY COMFORTABLE

51. If you were to submit a bid to curtail electricity during the weekday hours of 11 A.M to 5 P.M. through the DADRP, what is the minimum price, in $/MWh, at which you would offer to reduce electricity?

____________________ $/MWh

52. On average, how much of your electricity demand, in MWs, would your facility offer to reduce at this price during this period?

____________________ MWs

53. Has your facility ever registered for the ICAP Special Case Resource program, commonly referred to as SCR?

❑ 1. YES **(GOTO QUESTION 54)**
❑ 2. NO **(GOTO QUESTION 55)**
❑ 3. DON'T KNOW **(GOTO QUESTION 55)**

54. In which years did your facility sell its load curtailment or on-site generation output as a capacity resource in the ICAP/SCR program? (CHECK ALL THAT APPLY)

❑ 1. 2001
❑ 2. 2002
❑ 3. 2003

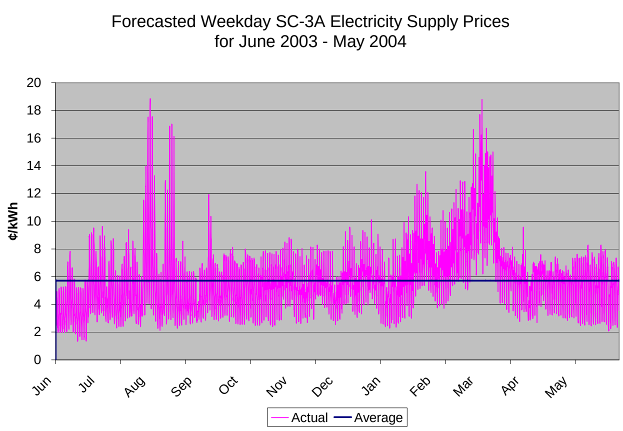
55. Would you be willing to participate in a follow-up interview within the next three weeks? If so, please indicate below. Interviews, which will last roughly 20 – 25 minutes, will be conducted over the phone with one of our staff members. If you indicate "Yes" below, then you will be entered into a drawing to win either a digital video camera or a weekend getaway to Niagara Falls each valued at $450,

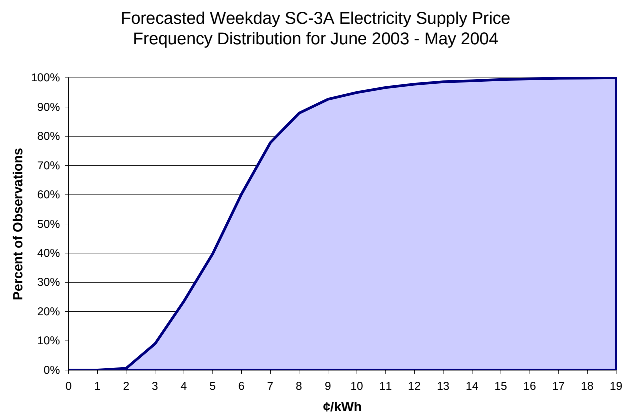
unless you subsequently refuse to schedule and complete the interview. The odds of winning are 1:50.

- ❑ 1. YES, I WOULD BE WILLING TO PARTICIPATE IN A FOLLOW-UP INTERVIEW
- ❑ 2. NO, I WOULD NOT LIKE TO PARTICIPATE IN ANY FOLLOW-UP INTERVIEWS

This is the last section of the survey; it takes about 15 minutes to complete and then you are finished.

In this section, we ask you to make a series of choices among different electricity hedging contracts that vary in how much price variation you are exposed to and the hedging premium you pay. In each case, you can elect to pay no hedging premium and face market-based hourly electricity prices.
To characterize the decision environment, suppose that day-ahead hourly electricity prices under Option 1 of SC-3A for June 2003 through May 2004 are forecasted to average around 5.7 ¢/kWh, but are subject to variation illustrated in the figures below. While generally below 10 ¢/kWh, prices may climb into the 15 – 20 ¢/kWh range during one or more days, usually, but not always in the summers, and have historically reached as high as 100 ¢/kWh for short periods.





In each of the following 19 questions, you are going to be shown a set of four (4) hedge contracts, each containing different levels of five hedge features, as follows:

1. The amount of your load the hedge contract covers;
2. The hours of the weekday covered by the hedge contract;
3. The months of the year covered by the hedge contract;
4. The Hedge design; and
5. The Hedge price and premium.

In each choice, select one of the hedge contracts, or the SC-3A unhedged alternative. Please indicate your choice by checking the appropriate box. It is very important that you select one choice for each of the 19 questions. An example pricing plan alternative is provided on the next page

Explanation of Contract Features and an example alternative

	Hedge Load	Covered Hours	Covered Months	Hedge Method	Hedge Price
Hedge 1	50%	12 Noon - 10 PM	Jun - Aug and Dec - Feb	Capped Price	7¢/kWh @ 10%

Hedged Load

- **The percentage of maximum demand that the hedge contract will cover**
- In the sample hedge contract above, 50% of your organization's maximum demand will be covered under the hedge.

Covered Hours

- **The hours of the weekday covered by the hedge contract. In the hours not covered, the SC-3A pricing plan applies.**
- In the sample hedge contract above, the hedge would cover electricity usage during the hours of 12 Noon through 10 PM.

Covered Months

- **The months of the year covered by the hedge contract. In all months not covered, the SC-3A pricing plan applies.**
- In the sample hedge contract above, the hedge would cover electricity usage during the months of June through August and December through February.

Hedge Method

- **The type of pricing method used in the hedge, either a *Capped Price* or *Average Price*. A *Capped Price* hedge limits the price your organization would pay for its electricity usage to always be below the indicated price threshold. An average price hedge effectively results in paying a flat rate.**
- In the sample hedge contract above, the hedge uses a Capped Price.

Hedge Price

- **The price at which the electric commodity is purchased and the total cost of the hedge in terms of the percent of your monthly SC-3A electricity bill.**
- Because the hedge method in the example above is a Capped Price, the Hedge Price of 7 ¢/kWh represents the highest price for electricity usage your organization would have to pay. If the hedge method were an "Average Price", then your organization would pay 7 ¢/kWh for the all of its electricity usage covered under the hedge contract. To purchase this hedge, it would cost your organization 10% of its monthly SC-3A electricity bill.

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 1

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	100%	75%	25%	
Covered Hours	12 Noon - 10 PM	6 AM - 12 Noon	6 AM - 10 PM	12 Noon - 6 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec - Feb	Jun - Aug	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	7¢/kWh @ 10%	6¢/kWh @ 15%	9¢/kWh @ 3%	8¢/kWh @ 5%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 2

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	50%	100%	25%	
Covered Hours	12 Noon - 6 PM	12 Noon - 10 PM	6 AM - 10 PM	6 AM - 12 Noon	
Covered Months	All Year	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Average Price	Capped Price	Capped Price	
Hedge Load	7¢/kWh @ 10%	6¢/kWh @ 15%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 3

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	100%	25%	50%	I wouldn't purchase any of these hedges.
Covered Hours	6 AM - 12 Noon	12 Noon - 10 PM	6 AM - 10 PM	12 Noon - 6 PM	
Covered Months	All Year	Jun - Aug	Jun - Aug and Dec - Feb	Dec- Feb	
Hedge Method	Capped Price	Capped Price	Average Price	Average Price	
Hedge Load	6¢/kWh @ 15%	7¢/kWh @ 10%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 4

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	75%	50%	25%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 6 PM	12 Noon - 10 PM	6 AM - 12 Noon	6 AM - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec- Feb	Jun - Aug	All Year	
Hedge Method	Average Price	Capped Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	9¢/kWh @ 3%	8¢/kWh @ 5%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 5

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	75%	50%	25%	
Covered Hours	12 Noon - 6 PM	12 Noon - 10 PM	6 AM - 12 Noon	6 AM - 10 PM	
Covered Months	Jun - Aug	Jun - Aug and Dec - Feb	All Year	Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	9¢/kWh @ 3%	8¢/kWh @ 5%	6¢/kWh @ 15%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 6

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	75%	50%	100%	
Covered Hours	6 AM - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	12 Noon - 10 PM	
Covered Months	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Capped Price	Capped Price	Average Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	7¢/kWh @ 10%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 7

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	50%	25%	100%	
Covered Hours	12 Noon - 6 PM	6 AM - 12 Noon	12 Noon - 10 PM	6 AM - 10 PM	
Covered Months	Jun - Aug	All Year	Dec - Feb	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	7¢/kWh @ 10%	8¢/kWh @ 5%	6¢/kWh @ 15%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 8

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	50%	100%	25%	
Covered Hours	6 AM - 12 Noon	6 AM - 10 PM	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec - Feb	Jun - Aug	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	6¢/kWh @ 15%	7¢/kWh @ 10%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 9

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	75%	25%	50%	
Covered Hours	12 Noon - 10 PM	12 Noon - 6 PM	6 AM - 10 PM	6 AM - 12 Noon	
Covered Months	Jun - Aug	Jun - Aug and Dec - Feb	All Year	Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	9¢/kWh @ 3%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 10

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	75%	50%	100%	
Covered Hours	12 Noon - 10 PM	6 AM - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	
Covered Months	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Average Price	Capped Price	Capped Price	
Hedge Load	8¢/kWh @ 5%	6¢/kWh @ 15%	9¢/kWh @ 3%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 11

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	50%	25%	75%	I wouldn't purchase any of these hedges.
Covered Hours	6 AM - 10 PM	12 Noon - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	
Covered Months	All Year	Dec - Feb	Jun - Aug and Dec - Feb	Jun - Aug	
Hedge Method	Average Price	Capped Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	7¢/kWh @ 10%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 12

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	100%	75%	50%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 10 PM	6 AM - 12 Noon	12 Noon - 6 PM	6 AM - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	All Year	Dec - Feb	Jun - Aug	
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	7¢/kWh @ 10%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 13

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	25%	100%	75%	
Covered Hours	12 Noon - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	6 AM - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	All Year	Dec - Feb	Jun - Aug	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	7¢/kWh @ 10%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 14

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	25%	50%	100%	
Covered Hours	6 AM - 10 PM	6 AM - 12 Noon	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	All Year	Dec - Feb	Jun - Aug	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	8¢/kWh @ 5%	9¢/kWh @ 3%	6¢/kWh @ 15%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 15

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	100%	25%	50%	
Covered Hours	6 AM - 12 Noon	6 AM - 10 PM	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec - Feb	All Year	Jun - Aug	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Capped Price	Capped Price	Average Price	
Hedge Load	8¢/kWh @ 5%	7¢/kWh @ 10%	6¢/kWh @ 15%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 16

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	75%	100%	50%	
Covered Hours	6 AM - 12 Noon	12 Noon - 6 PM	6 AM - 10 PM	12 Noon - 10 PM	
Covered Months	Dec - Feb	All Year	Jun - Aug	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	9¢/kWh @ 3%	7¢/kWh @ 10%	6¢/kWh @ 15%	8¢/kWh @ 5%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 17

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	25%	100%	75%	I wouldn't purchase any of these hedges.
Covered Hours	6 AM - 10 PM	6 AM - 12 PM	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Jun - Aug	Dec - Feb	All Year	
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	8¢/kWh @ 5%	7¢/kWh @ 10%	6¢/kWh @ 15%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 18

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	100%	25%	75%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 6 PM	6 AM - 12 PM	12 Noon - 10 PM	6 AM - 10 PM	
Covered Months	All Year	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	
Hedge Method	Average Price	Capped Price	Capped Price	Average Price	
Hedge Load	7¢/kWh @ 10%	6¢/kWh @ 15%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 19

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	25%	100%	50%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 10 PM	6 AM - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	
Covered Months	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	All Year	
Hedge Method	Average Price	Capped Price	Average Price	Average Price	
Hedge Load	7¢/kWh @ 10%	9¢/kWh @ 3%	8¢/kWh @ 5%	6¢/kWh @ 15%	
Check only one choice	☐	☐	☐	☐	☐

Appendix C: Hypotheses for NMPC SC-3A Demand Modeling

No.	Null Hypothesis	Testing Method	Data Needed	Survey Question
	Changes in Response due to Price Timeline			
1.1	No structural change in customer responsiveness across introduction of NYISO prices, summer 2000 NYISO price spikes, and introduction of PRL Programs (price regimes)	Chow Test or Dummy Var in regression	NMPC price data	
	Firmographic Effects			
2.1	Degree of responsiveness (elasticity) is unaffected by time of peak demand	Demand Elasticity Model (or ANOV)	Define peak demand from meter data and survey	7
2.2	Degree of responsiveness (elasticity) is unaffected if large industrial or small commercial classification	Demand Elasticity Model (or ANOV)	Define type and size from survey and meter data	3
2.3	Degree of responsiveness (elasticity) is unaffected by level of load factor	Demand Elasticity Model (or ANOV)	Define load factor from meter data	
2.4	Degree of responsiveness (elasticity) is unaffected if customer's electricity costs are a large percentage of total costs or not	Demand Elasticity Model (or ANOV)	Electricity costs identified via survey	3
2.5	Degree of responsiveness (elasticity) is unaffected if customer has multiple shifts or not	Demand Elasticity Model (or ANOV)	Number of shifts identified via survey	10
2.6	Degree of responsiveness (elasticity) is unaffected if customer has high degree of production flexibility or not	Demand Elasticity Model (or ANOV)	Production flexibility identified via survey	Removed
2.7	Degree of responsiveness (elasticity) is unaffected if customer has periods of high business activity or not	Demand Elasticity Model (or ANOV)	Production schedule identified via survey	12, 13
2.8	Type of response (forego vs. shift) is unaffected by Business classification	Chi-Square (or ANOV if response type is continuous)	Define type of business from survey data. Assess response characteristic from demand model.	3
	Method of Response			
3.1	Proportion of customer's using on-site generation vs. other methods of response	Descriptive Statistic	On-site generation identified via survey	25
3.2	Degree of responsiveness (elasticity) is unaffected by use of on-site generation vs. other methods of response	Demand Elasticity Model (or ANOV)	On-site generation identified via survey	25
3.3	Degree of responsiveness (elasticity) is unaffected by investments in load-shifting technology or not	Demand Elasticity Model (or ANOV)	Load-shifting technology investment identified via survey	31, 33
3.4	Degree of responsiveness (elasticity) is unaffected by process type (batch vs. continuous)	Demand Elasticity Model (or ANOV)	Process type identified via survey	11
	Experience with HIPP			
4.1	Proportion of people choosing Option 1 vs. Option 2 is unaffected by prior experience with HIPP	Chi-Square	Prior experience w/ HIPP and choice of Option 1 or 2 identified via survey	14
4.2	Degree of responsiveness (elasticity) is unaffected by prior experience with HIPP	Demand Elasticity Model (or ANOV)	Prior experience w/ HIPP and choice of Option 1 or 2 identified via survey	14
4.3	Degree of responsiveness (elasticity) is unaffected by the number of years on an RTP (HIPP/SC-3A) rate	Demand Elasticity Model (or ANOV)	Number of years on an RTP rate identified via survey	14
	Response as a Function of Prices			
5.1	Prices must reach a self-reported or analytically determined threshold before significant response is undertaken	Descriptive Statistic	Price threshold identified via survey or analytically from the data	27
5.2	Prices must reach a self-reported or analytically determined percentage above average before significant response is undertaken	Descriptive Statistic	Percentage price increase identified via survey or analytically from the data	Removed
5.3	Degree of responsiveness (elasticity) is unaffected by the voltage level	Demand Elasticity Model (or ANOV)	Voltage level based on NMPC data	
5.4	Degree of responsiveness (elasticity) is unaffected by the location in the state	Demand Elasticity Model (or ANOV)	Location in the state based on NMPC data	
	Effects of Hedging Contracts			
6.1	Degree of responsiveness (elasticity) is unaffected by holding a hedge or not	Demand Elasticity Model (or ANOV)	Hedge purchase identified via survey	39, 41
6.2	There is no difference in the number of people choosing between Option 1 vs. Hedged Service (Option 2 or an independent contractor) at inception of SC-3A	Descriptive Statistic	Hedge purchase identified via survey	39, 41
6.3	The difference in the number of people choosing to purchase a hedge contract is unaffected by the "three price regimes"	Chow Test or Dummy Var in regression	Hedge purchase identified via survey	39, 41
6.4	Degree of responsiveness (elasticity) is unaffected by the proportion of load hedged	Demand Elasticity Model (or ANOV)	Hedge purchase identified via survey	39, 41
	Interaction between RTP and PRL Programs			
7.1	The proportion of people choosing to participate in a NYISO PRL program is unaffected by the choice to hedge or not	Chi-Square	PRL program participation identified via survey	39, 41, 42, 45, 53
7.2	The proportion of customers chosing to participate in DADRP is unaffected by degree of responsiveness (elasticity)	Chi-Sqyare	PRL program participation identified via survey	45
7.3	The proportion of customers chosing to participate in ICAP/SCR is unaffected by degree of responsiveness (elasticity)	Chi-Squate	PRL program participation identified via survey	53
7.4	The proportion of customers chosing to participate in EDRP is unaffected by degree of responsiveness (elasticity)	Chi-Squate	PRL program participation identified via survey	42

Appendix D: Economic Theory of Discrete Choice Models

The modeling of the stated preferences of customers for hedging load can be accomplished within a random utility formulation. This was facilitated in Part II of the customer survey by having respondents select individual choices from choice sets involving choices among four hedge products with different values for five features and a "no program" alternative.[1] Accordingly, we model this choice situation as though the i^{th} customer is faced with J choices, and the utility of the choice j is given by:

(1) $U_{ij} = \beta' Z_{ij} + \varepsilon_{ij}$.

where
U_{ij} = the utility of customer i making choice j utility;
Z_{ij} = is a vector of program features;
β' = vector of parameters to be estimated; and
ε_{ij} = an error term.

If the customer chooses program feature j, then it is assumed that U_{ij} is the maximum of the utilities for all the J alternatives. The statistical model is driven by the probability that choice j is made:

(2) Prob $[U_{ij} > U_{ik}]$ for all $k \neq j$.

This indicates the probability that the utility of choice j for individual i is greater than the utility of any other choice k.

To make this model operational, we must make an assumption about the distribution of disturbances, ε_{ij}. Following McFadden (1973) and Greene (1990), we let Y_i be a random variable for the choice made. It can be shown that if (and only if) the disturbances are independent and identically distributed according to a Weibull distribution,

(3) $F(\varepsilon_{ij}) = \exp(-e^{-\varepsilon ij})$,

then, we can express the probability of choice j by individual i (Prob $[Y_i = j]$) as:

(4) Prob $[Y_i = j] = \exp[\beta' Z_{ij}] / \{\sum_j [\exp \beta' Z_{ij}]\}$,

is called the conditional logit model. As in the case of the binary logit model, this conditional logit model is estimated by the method of maximum likelihood but uses the SAS procedure PROC PHREG due to its ability to handle tied data (Allison, 1999).

[1] The conjoint survey is included in Appendix B. The features used in the choice sets represent the major characteristics of a hedge contract. The range in values used in creating the choice sets reflect those ascertained by the research team as feasible, given the team's experience in this area and through discussions with retail suppliers offering such products.

Appendix E: Methods for Estimating Response in Electricity Usage to Real Time Prices

Introduction

This appendix provides a detailed discussion of the economic model used to estimate Niagara Mohawk Power Company's industrial and commercial customers' response to electricity prices. Based on these customers' circumstances, electricity use is modeled as the derived demand for electricity as an input into the productive and business processes of firms. Consequently, the appropriate economic specification is to characterize how firms make decisions on how much electricity to use to minimize their cost of production. Following well-established conventions, electricity is portrayed as two inputs differentiated by the time in which it is deployed; peak or off-peak. This specification poses several conceptual issues that need to be resolved in using real time pricing (RTP) data to estimate price responsiveness, which are discussed in some detail. The final model used to estimate price elasticities, referred to as the Constant Elasticity of Substitution (CES), is a highly structured and theoretically consistent representation of the trade-offs made by firms between peak and off-peak electricity usage. The CES model also provides a means for quantifying how firms alter the relative use of electricity in peak and off-peak periods.[2]

We selected the CES specification because it provided a tractable means for estimating substitution elasticities given time, resource, and data availability constraints. But, the CES model approach also imposes certain rigidities on assumed customer behavior; most notably that shifting opportunities are limited to the day's peak and off-peak periods and that the elasticity of substitution is constant. These assumptions may not fully reflect how some customers actually respond. Thus, we describe two alternative, more complex specifications of the demand model that allow customers to shift usage to the subsequent day (see Attachment B) or allow elasticities to vary with the nominal level of the change (see Attachment A). These models provide a means to test additional hypotheses about factors affecting customers' price responsiveness and could represent useful areas for additional research and analysis of the NMPC RTP customer database.

Finally, we discuss an approach that can be used to characterize different types of customer demand response behavior. The survey administered to SC-3A customers revealed three distinct response behaviors: load shifting, foregoing discretionary usage, and conservation. If customers shift their activity and usage from the peak to the off-peak period, holding output constant, then that behavior is fully captured by the CES model specifications, which accurately characterizes the response in terms of reduced on-peak usage. However, if customers forego "discretionary" usage during the high priced (peak) period (e.g., by raising thermostat set-points or turning off some lights) and still hold output constant, then the CES model does not fully capture the resulting impact in reduced peak consumption. While the ratio of peak to off-peak usage changes (declines),

[2] The greater the ability of a firm to adjust output to accommodate relative electricity prices, the larger its reduction in peak usage when SC-3A day-ahead prices increase.

the estimated substitution elasticity underestimates the actual peak usage reductions. Finally, "conservation," defined as an equal proportional reduction in both peak and off-peak usage during days of high prices, yields a substitution elasticity of zero, which again results in the underestimation of actual peak reductions. Following Patrick (1990), we developed a Load Response Characterization (LRC) model that determines whether customers' behavior is most consistent with load shifting, foregoing, or conservation. We take results from the LRC model to develop and apply an adjustment factor to correct for the underestimation of peak load reduction in estimating the aggregate demand response potential of NMPC SC-3A customers.

The Electricity Demand Model

Our focus is on the use and allocation of electricity inputs by industrial and commercial customers and the quantification of their electricity usage response to changes in price. Therefore, the most appropriate theoretical economic model should attempt to describe how firms maximize profit, or equivalently, how they minimize cost for producing a given level of output. Further, this economic problem involves a three-level profit or cost function, because the underlying production function is assumed be separable in electricity usage.[3] The practical implication of separability in production is that choice of cost minimizing input levels (peak and off-peak electricity use) within any sub-function (the total electricity usage relationship) depends only on prices of those inputs. Thus input demands and price response elasticities can be derived from the sub-function alone, without explicit knowledge of the overall output of the firm or its use of other inputs.

At the first level of cost minimization, we allocate weekday electricity usage between time periods during the day in which electricity prices differ, and/or the values of electricity to the firm differ. The second level involves allocating monthly usage between weekdays and weekends, and the third determines overall electricity expenditures as a proportion of total costs, reflecting the relative demand for electricity in relation to all other inputs in the firm's production process.

Given this theoretical specification, the corresponding empirical approach for estimating customers' response to changes in electricity prices would be to estimate all three levels of electricity demand within the same modeling framework. This would provide an in-depth characterization of the role and value of electricity in the firm's operation. Unfortunately, this is seldom possible. Estimating the latter two stages requires data on the firm's output level, its usage of inputs other than electricity, and output and input

[3] For a production function or utility function to be weakly separable in any partition of its arguments, the marginal rate of substitution between any two inputs or goods in a separable subset is independent of all inputs or goods that are not in the subset (Chambers, 1988, pp. 45-46). In other words, any function in n variables, $f(x) = F(x_1, \ldots, x_n)$, that is separable in a partition x^1 through x^m, where x^i is a vector representing a subset of the n variables, can be written as $f(x) = F(f^1(x^1), \ldots, f^n(x^n))$. Each of the sub-functions can be treated as an aggregate input or consumption bundle—essentially a production or utility function in and of itself. Therefore, it is legitimate to think of production or consumption occurring in two steps. To use the example of a production function, inputs in the sub-vector are combined to create the aggregate inputs in the first step. In the second step, these aggregate inputs are used to produce the output via the macro production function.

prices available at the same level of granularity as electricity prices (i.e., hourly values). Even if such data were readily available, customers would be reluctant to provide detailed production and price data, given confidentiality and competitiveness concerns.

The alternative is to use this theoretical model of derived factor demand as a general guide for specifying the empirical model, which characterizes the first stage of the model (i.e., the choice of the level of peak and off-peak electricity usage given prevailing prices). Moreover, survey information collected from firms provides a means for expanding the characterization, and identifying important drivers that distinguish customers according to their inclination to respond to price changes. This approach is consistent with the preponderance of past empirical work on modeling firm response to varying electricity prices.[4]

Defining the Electricity Commodity

In the literature, it is generally agreed that the appropriate representation of how customers make peak and off-peak electricity usage decisions is as a firm's factor demand system (Patrick, 1990; Braithwait, 2000). However, developing the appropriate empirical specification for examining hourly pricing programs for retail electricity customers is challenging because of the subjectivity in defining the electricity peak and off-peak commodities. The issue is essentially the same for examining TOU and RTP rates, but they are normally dealt with differently because of the way in which the data are generated. TOU service involves a price schedule, with different prices for specified, mutually exclusive and exhaustive time periods. Consequently data for TOU customers involve usage data only for the collective peak hours (in a month, typically) and the corresponding off-peak hours. TOU prices differ between the peak and off-peak periods, but these prices are the same for all days in the month.[5] Conversely, data from RTP programs include hourly usage data and price data that differ by day and hour.

In the case of TOU usage data, defining the energy commodities by the peak and off-peak usage aggregates is straightforward, because the TOU rate creates that distinction. Customers face a separate price for each of these two electricity commodities, defined by the peak and off-peak periods, and the price is constant for each commodity. This is

[4] This basic model is conceptually similar to the consumer demand model discussed by Braithwait (2000) in a recent study of residential TOU rates in New Jersey. His data came from a pilot study implemented by GPU Energy in summer 1997. In that study, Braithwait begins the theoretical analysis with the maximization of a three-level indirect utility function, which is assumed separable in electricity consumption. At the first level, weekday electricity usage is allocated between time periods in which electricity prices differ. The second level allocates monthly usage between weekdays and weekends, while the third determines overall electricity expenditures as a proportion of income, reflecting the relative demand for electricity in relation to all other goods. Empirically, he focuses exclusively on the first stage, and goes on to derive demand functions using both the constant elasticity of substitution (CES) and Generalized Leontief (GL) forms. In an earlier paper, Caves, *et al*. (1984) estimate a demand model that includes all three stages of electricity demand based on data from five experimental implementations of residential TOU rates in the United States. It is perhaps the only study that looks at all three stages of electricity demand, and one of only a handful of studies that consider more than just the within-day energy demand (see also Herriges *et al*. 1993; and Schwarz et al., 2002).
[5] Prices may change from season to season.

consistent with an economist's notion of distinct commodities: their prices differ so they have different values to the firm. However, with TOU data, there is no price variation across days against which to measure demand response for any individual customer. To introduce price variability, most studies of TOU rates have pooled data for different customers participating in several separate TOU rates, or data are pooled across several treatments for a given rate experiment (Patrick, 1990; Braithwait, 2000; Caves et al, 1984).[6] In other studies, different TOU treatments were implemented to provide price variations representative customers are defined for the separate programs (Charles River, 2004).

Data for RTP customers is almost too extensive. If one truly believes that industrial and commercial RTP customers can "load" follow on an hourly basis and adjust usage to different hourly prices, then each hour's electricity use is indeed one of 24 distinct commodities. Herriges et al. (1993) adopted this strategy in analyzing Niagara Mohawk Power Corporation's initial RTP pilot program, called Hourly Integrated Pricing Program (HIPP), where the price change in any hour causes usage shifts in other hours of the same day according to an Allen partial elasticity of substitution derived from a nested CES model. This model accounts for inter-day shifts as well, which is important when firms respond by moving production to another day.

Generally however, analysts have resorted to creating aggregate electricity commodities by grouping hours of the day. For example, in an effort to identify demand elasticities for hourly electricity commodities that are identically priced, Caves *et al*. (1987) identify six separate commodities for customers facing a six-hour peak pricing period, where two three-hour segments of the peak period are separated by a single hour. These peak hours are divided into two separate commodities—one two-hour commodity and one four-hour commodity. The remaining hours are aggregated into four separate commodities; all are priced the same. They argue that this sub-aggregation of the peak is needed to examine the existence of needle peaking (e.g. large increases in consumption in hours adjacent to the peak). Similarly, Patrick (1990) describes several analyses conducted on pilot data from TOU pilots conducted in the 1970s, and utilizes the CES formulation in his study of these program results.

Utilizing a fully disaggregated model, like the one adopted by Herriges *et al*. (1993), with 24-separately priced commodities, is advantageous in that it does not impose any specific structure on behavior, and therefore allows for a variety of responses that reflect different customer circumstances. Moreover, it provides a means for tracing exactly how the load shape is adjusted, which is important if the response to high prices in some hours results in shifting that peak to another hour, creating a needle peak that exceed the typical peak hour's usage, instead of spreading it out over several hours, or foregoing consumption

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[6] Braithwait (2000) was able to examine price responsiveness of customers in two different ways because of the nature of the residential TOU rate. The first was to estimate substitution elasticities between peak and off-peak periods. He assumed that for any given day, there were only two electricity commodities. His second approach was to estimate substitution elasticities among three separate electricity commodities—usage during peak, shoulder, and off-peak periods. As one might expect, the substitution elasticities between peak and shoulder periods and shoulder and off-peak were lower than for peak to off-peak periods.

altogether. As part of this Appendix (see Attachment B), we outline this model as a guide for future research. However, such an elaborate specification was beyond the resources of this project.

In this study, we employed a simpler, single-stage constant elasticity of substitution (CES) model to analyze the behavior of SC-3A customers, utilizing two aggregate commodities, peak and off-peak consumption of electricity. The model allows price responsiveness to differ by the size of the price differences, but not by the nominal level of the prices themselves (thus the constant designation). To specify the CES model, we split the day into two demand periods—a high priced period and a low priced period. The "demand inducing" price for each commodity is assumed to be the average hourly price in the relevant block of hours. By interpreting the data in this way, we are able to study the demand response behavior of firms between "peak" and "off-peak" times in a consistent fashion. But, how are the peak and off-peak defined? To qualify as distinct peak and off-peak commodities, the day must be divided so that the resulting consumption aggregates support the firm's desired daily output, that could be substituted for one another to achieve that output, and that result in commodity prices that are sufficient in level to induce such substitution. While all SC-3A customers effectively face the same prices, those prices vary in their daily pattern for summer to winter, and even among weekdays in the same season. However, there are distinct delineations; high prices predominantly occur in consecutive afternoon hours, the timing and duration of which are the main sources of variation.[7] This suggests that the peak should comprise the afternoon hours, but exactly which depends on the pattern and level of the prices themselves.

The model was estimated for several alternative peak periods that differ in length and the time period they cover, to allow the data to determine the extent to which firms view electricity as a distinct hourly commodity or as one that involves hourly aggregates.[8]

We explored several alternative definitions of the peak period, which were defined as the hours between Noon to 5:00 p.m., 1:00 p.m. to 5:00 p.m., and 2:00 p.m. to 5:00 p.m.; each specification is used to estimate the demand equations, as discussed below.

[7] SC-3A prices are differentiated by NYISO zone and by the delivery transmission level (transmission, primary, secondary). The latter amount to differences in the loss factor applied to NYISO prices. The main zonal price difference is for the Capital region, which exhibits somewhat higher prices than the rest of the NMPC service territory. However, because in the CES formulation, the substitution elasticity depends on relative price changes, and not on their nominal level, customers in this region can be pooled with those in other zones in model estimation.

[8] Rather than specifying this peak period for the same hours of the day regardless of prices, an alternative would be to define a "dynamic" peak period, whereby the definition of peak varies each day. This would be accomplished by defining a peak period of a specified length, say three-hours for example, as the three hours of the afternoon where the consecutive three-hour average prices are the highest. By defining the customer "peak" in this way, we assume that customers are willing to reduce load for a three-hour period every day, but those three hours are determined to be those consecutive with the highest average prices. This seems a reasonable alternative behavioral assumption to test since the firms are given the 24-hour prices a day in advance, but one that was beyond the scope of this study.

The Single-Stage CES Model Specification

To begin the model development, we define a firm's production function that is separable in its peak and of-peak electricity inputs as:

(1) $Q = F(x_1, x_2, \ldots, x_n , q(k_p, k_o))$,

where Q is output of the firm, x_i are inputs other than electricity (labor, materials, etc.) and k_p and k_o are aggregate electricity use (kWh) in peak and off-peak periods, respectively. Assuming that electricity use is separable from other inputs, and employing the CES specification of the production relationship, we can write the electricity sub-function as:

(2) $q = [\, \delta\, (k_p)^{-\rho} + (1-\delta)\, (k_o)^{-\rho}\,]^{-1/\rho}$

In this function, q is an aggregate electricity input that exhibits constant returns to scale (Moroney, 1972; and Ferguson, 1969). The parameter δ reflects the natural peak kWh intensity of production. The parameter ρ measures the transformation of the elasticity of substitution between peak and off-peak electricity use, where $\sigma = 1/(1 + \rho)$.[9] This elasticity of substitution is constant regardless of the levels of energy use or levels of output.

To identify the price responsiveness of electricity demand between peak and off-peak periods, it can be shown that the ratio on input use is a function of the inverse of the price ratio for the inputs and the parameters of the of δ and σ. This relationship is derived from a model to minimize the electricity cost:

(3) Electricity cost = $P_p\, K_p + P_0\, K_0$,

to produce a given level of the electricity aggregate from equation (1). By manipulating the first-order conditions for this minimization problem, the marginal technical rate of substitution (MTRS), which is the ratios of the marginal products of inputs, is set equal to the price ratio. The marginal products for peak and off-peak electricity are then as follows (see Miller *et al*. (1975) for the most transparent derivation):

(4a) $\partial q \,/\, \partial k_p = \delta\, (q \,/\, k_p)^{1/\sigma}$ and

(4b) $\partial q \,/\, \partial k_0 = (1 - \delta)\, (q \,/\, k_0)^{1/\sigma}$.

The ratio of these two equations is the marginal technical rate of substitution (MTRS) of k_0 for k_p:

(5) MTRS = $[\, \delta \,/(1 - \delta)\,]\, (k_0 \,/\, k_p)^{1/\sigma}$.

[9] The algebra needed to derive this relationship, along with the derivation of the elasticity of substitution, is found in Ferguson (1969, pp. 103-04) and is not repeated here.

The necessary conditions for cost minimization require that MTRS be set equal to the ratio of input prices:

(6) $[\ \delta /(1 - \delta)\ ]\ (k_0 / k_p)^{1/\sigma} = p_p / p_0$

where p_p and p_0 being peak and off-peak prices, respectively. Solving this relationship for the relative intensity of electricity use between peak and off-peak periods, we have:

(7) $k_p / k_0 = \{[\ \delta /(1 - \delta)\ ]\ [p_0 / p_p\ ]\}^{\sigma}$.

The ratio of peak to off peak electricity usage is a function of the inverse price ratios (i.e., the ratio of off-peak to peak prices). The parameters δ (intensity) and $^{\sigma}$ (transformation) characterize the extent to which peak and off-peak usage are substituted as the input price ratio varies.

A Strategy for Estimating the CES Model

If we multiply the right-hand-side of equation (7) by an appropriate error term (ε), and take the logarithms of both sides, we can obtain an unbiased, minimum-variance estimate of σ using ordinary least squares (OLS):

(8) $\ln [\ k_p / k_o\ ]= \sigma \ln [\ \delta /(1 - \delta)\ ] +\sigma \ln [p_0 / p_p\ ] + \ln \varepsilon$.

The parameter σ measures the proportional change in the ratio of electricity use in peak and off-peak periods due to a percentage change in the inverse price ratio. For this production function to be well behaved, Ferguson (1969) shows that $0 < \sigma < \infty$.[10] The higher σ is, the more responsive (in terms of shifting from one period to another) energy use is to changes in relative prices between peak and off-peak periods. For example, if $\sigma < 1$, then as the price ratio changes by one percent, the ratio of peak to off-peak energy use changes by less that one percent. Conversely, for $\sigma > 1$, the ratio of peak to off-peak energy use changes by more than one percent as the inverse price ratio changes by one percent. Analyses of RTP service have produced substitution elasticity values for customer segments that range from 0 to 0.75 (Neenan Associates, 2003; King, 1994).

The estimated constant term from equation (8) is,

(9) $a = \sigma \ln [\ \delta /(1 - \delta)\ ]$.

To recover δ for a given estimate of σ we know that $a / \sigma = \ln [\ \delta /(1 - \delta)\ ]$. Rearranging terms yields the following:

[10] This relationship shows that σ is the proportional change in the use of electricity in the peak period relative to the off-peak period (holding output, in this case the electricity aggregate, constant), as the inverse price ratio increases or decreases by one percent (see Ferguson, 1969, pp. 103-04).

$(10.a)\ [\ \delta/(1-\delta)\ ] = e^{a/\sigma}$,

$(10.b)\ \delta = (1-\delta)\ e^{a/\sigma}$,

$(10.c)\ \delta = e^{a/\sigma} - \delta\ e^{a/\sigma}$, and

$(10.d)\ \delta = (e^{a/\sigma}) / (1 + e^{a/\sigma})$.

We are able to identify all the parameters of the CES function, with the exception of δ, utilizing an Ordinary Least Squares estimator. The intensity parameter (δ) may be critical in simulating firm behavior as part of the process of designing price-responsive load programs.

Empirical Specification of the CES Demand Model

For empirical estimation, it is important to define exactly how the variables used in the regression analysis are calculated from the data. From equation (8), one needs to have the ratio of peak to off-peak electricity use. For each weekday, t, and firm or group of firms, m, define:

k_{ptm} = peak kWh;

k_{0tm} = off-peak kWh;

p_{ptm} = average hourly peak price / kWh; and

p_{0tm} = average hourly off-peak price/kWh.

Many of the firm-level variables collected in the customer survey are included in the initial specification of this model. To illustrate how this is done without including unnecessary algebra, it is sufficient to focus here only on firm-level dummy variables, the weather index and whether or not the firm is a manufacturing company. The firm-level dummies are included only as intercept shifters. However, the weather index and the manufacturing dummy are included as both an intercept and a slope shifter (see Attachment C for discussion of the weather index variable). In the actual estimated model, other variables are included in a similar fashion.

The full model can now be specified as (for all observations across time t):

$(11)\ \ln(k_{ptm} / k_{0tm}) = a + \sum a_m D_{tm} + b\ w_{tm} + d\ \ln(p_{0tm} / p_{ptm})$

$+ \{b_m D_{tm} [\ln(p_{0tm} / p_{ptm})]\} + g\ w_{tm} [\ln(p_{0tm} / p_{ptm})] + \ln e_{tm}$

In this most general form, both the distribution parameter, δ, which is embodied in the parameter 'a' of equation (11) differs by firm and weather (w_{tm}).[11] That is for $D_{tm} = 1$ (i.e., a manufacturing firm) we have:

(12) $a_{tm} = a + a_m + b\ w_{tm}$.

If the firm is not a manufacturing company, the term a_m drops out of equation (12). In this specification, there are separate intercepts for each firm and each value of the weather index. These variables affect the relative level of usage between peak and off-peak periods, but not the rate at with usage responds to price.

More important, the price response, σ, also depends on some of these other variables. For $D_{tm} = 1$ (i.e., a manufacturing firm), we have the relevant logarithmic partial derivative given by:

(13) $\partial\ [\ln\ (k_{ptm} / k_{0tm}\ )\ ] / \partial\ [\ln\ (p_{0tm} / p_{ptm}\ )\ ] = \sigma_{tm} = d + \{b_m\ D_{tm}\} + g\ w_{tm}$.

This specification implies that price response differs by whether the firm is a manufacturing firm and weather.[12] For the non-manufacturing firm, $\{b_m\ D_{tm}\}$ drops out of the equation. Normally b_m and σ_{tm} would be evaluated at the means of w_{tm}. They could also be evaluated at monthly means etc. During the summer peak months (i.e., June through September), one would expect extremely hot weather to reduce a firm's ability to substitute electricity between peak and off-peak periods. Thus, we would expect g to be negative. Depending on the characteristic being measured by D_{tm} (e.g., whether the firm is in manufacturing), the estimate of parameter a_m and σ_m could be expected to be positive or negative.

One potential disadvantage of the CES specification is that the elasticity of substitution is assumed to be constant (i.e., invariant with respect to initial peak relative to off-peak electricity usage or to the initial relative prices). It is conceivable that some customers are more price-responsive at higher prices. For example, a 10% increase in the peak price from \$0.50 to \$0.55 per kWh might induce a bigger demand response by some customers than would a comparable percentage increase at much lower prices (e.g., \$0.05 to \$0.055 per kWh). This might be the case because a customer incurs fixed costs to curtail, and therefore requires that a certain price threshold be exceeded before they are willing to curtail or because they realize increasing marginal net returns for increased curtailments. This limitation may be addressed by using an Indirect Generalized Leontief Cost Function (see Attachment A).

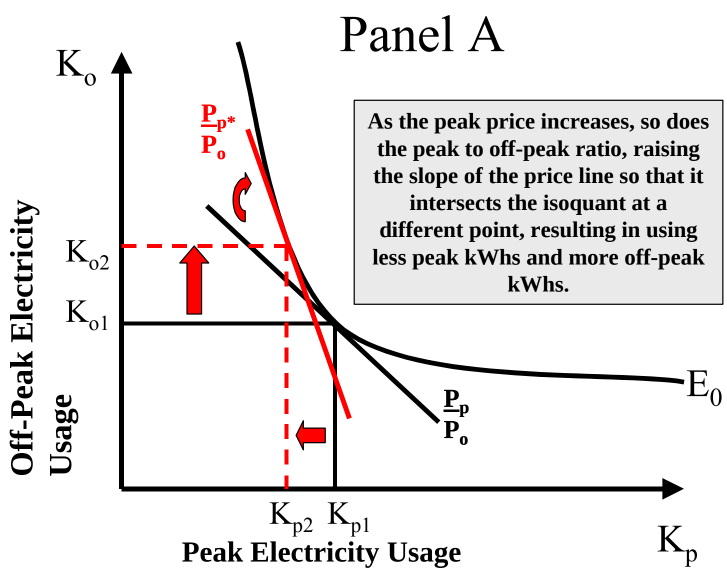
[11] See Attachment C for a definition of the weather index.

[12] This is a model in which the elasticity of substitution is affected by production processes, weather, or other factors specific to the firm, Z_i. It is a simple extension of the CES model, and as Caves and Christensen (1980) demonstrate algebraically that the modification is accommodated in the conceptual model by replacing ρ in equation (1) with $\rho + \sum_i \gamma_i Z_i$.

Electricity Conservation vs. Shifting

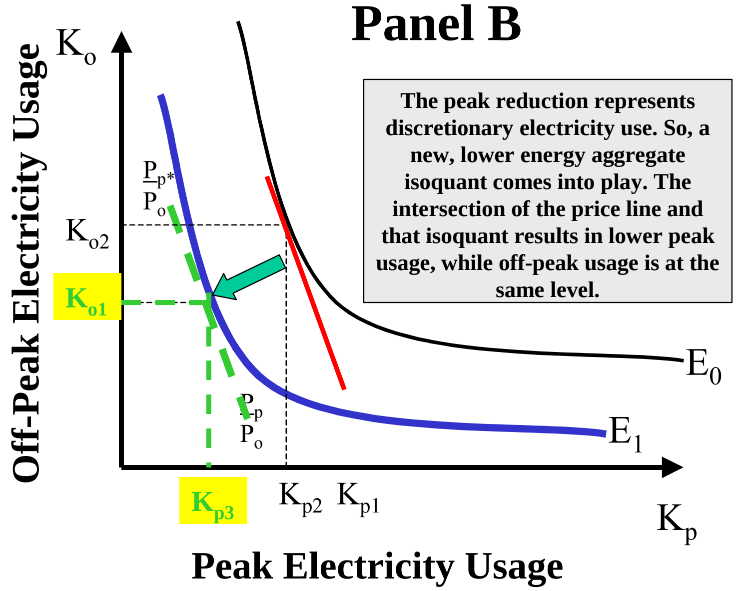
The CES model assumes that the electricity aggregate of the firm does not change in response to price differences – only the relative peak and off-peak electricity inputs in the production process are altered. Some SC-3A customers indicated in the customer survey that they simply forego using certain electrical equipment or end uses when asked to respond to either system emergency or high prices (e.g., turn off lights).

This practice violates the underlying assumption of a CES model that assumes the energy aggregate involves only peak and off-peak energy. The conservation response to price increases suggests that there is another force to be accounted for in the derived factor demand system; customers can forego peak and off-peak usage (e.g., reduced comfort level) for the aggregate electricity input while maintaining firm output. In other words, some customers forego usage altogether, rather than shifting from peak to off-peak periods. In this situation, our estimate of the elasticity of substitution will correctly characterize the shifting effect, but under-estimate the nominal level of the reduction in peak usage.



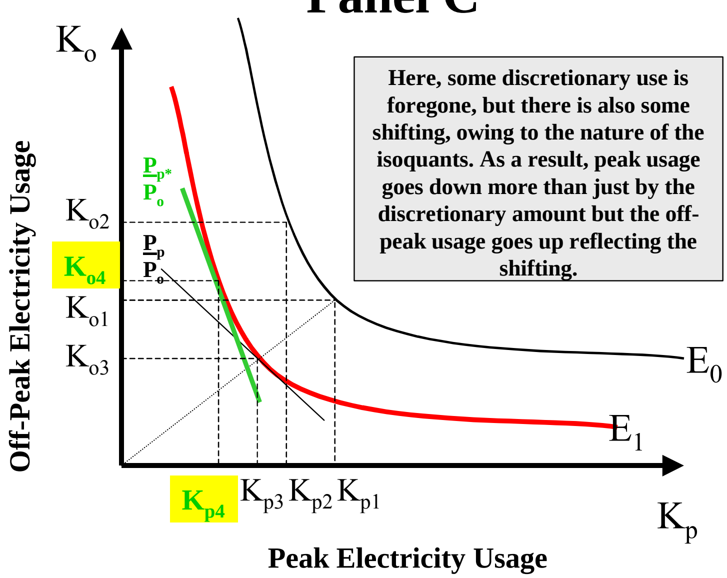
To see this more clearly, consider Panel A. The curve E_0 represents combinations of the inputs K_{p1} and K_{o1} that produce an energy aggregate that support the firm's desired (and constant) output. At the expected price levels of P_p and P_o, the firm would be expected to use K_{p1} and K_{o1} of peak and off-peak electricity respectively (which is the intersection of the price line in Panel A, with slope Pp/Po, and the isoquant E_0). When the peak period price changes to P_{p*}, the price line's slope increases, and it intersects the isoquant E_0 at a different point, which results in lower peak electricity usage and more off-peak electricity to hold the energy aggregate and output constant. The substitution elasticity measures these input substitutions.

Panel B



But what if the customer responds to high peak prices by foregoing peak consumption altogether (e.g., a customer elects to reduce occupant comfort by increasing the thermostat setting by 2-4 degrees while still maintaining the firms' output)? As a result, the firm requires less of the energy aggregate to maintain its output level. Since the energy aggregate is lower, a new isoquant now represents the input tradeoff possibilities, which can be illustrated by a shift to the isoquant to E_1 in Panel B. In this simplified case, the shift is such that the off-peak usage stays the same (K_{o1}), while peak usage declines (K_{p3}). In this case, the response is achieved solely by foregoing peak usage. The overall cost of production is still minimized allowing the firm to maintain the same level of output. However, the estimated substitution elasticity, which is based on the energy aggregate remaining constant (i.e., so that substitution is along isoquant E_o), does not reveal the actual nature of the response.

Panel C



Depending on the shape of the isoquants, which reflect the firm's underlying production processes, it is possible to observe outcomes that involve both load shifting and foregone consumption. In Panel C, the shape of E_0 and E_1 (the isoquants have a different shape) is such that the shift in the price lines result in a different peak (K_{p4}) and off-peak (K_{o4}) level compared to the situation described in panel B. The foregone usage lowers the peak and the off-peak usage, but there is also shifting that further reduces the peak usage and increases the off-peak usage.

To summarize, the surveys administered to NMPC SC-3A customers confirmed that while some customers respond by shifting, others forego discretionary usage, and some do both. Accordingly, while the CES model we specify will correctly characterize shifting behavior in response to price changes, it will underestimate the amount that peak load is reduced by the extent to which customers forego consumption. Fortunately, a means is available for reconciling these behaviors and estimating the final peak reduction amount for a given price change.

Load Response Characterization (LRC) Model: Empirical Specification of Conservation vs. Load Shifting

In addition to measuring the elasticity of substitution between peak and off-peak electricity consumption, it is essential to fully characterize the kind of behaviors that customers engage in to accomplish that change. Specifically, we want to distinguish pure load shifting from responses that involve foregoing consumption.[13] In this section, we describe the Load Response Characterization (LRC) model, which is an empirical approach for adjusting the substitution elasticity to accommodate behaviors other than load shifting. We use the LRC model results as part of our effort to estimate customer's expected reductions in peak usage for a given price change (i.e., demand response).

We employ an analytical framework similar to that used by Patrick (1990) in his analysis of the results of electricity TOU pricing pilot programs, which primarily targeted commercial customers. Patrick postulates that customers can respond by shifting load, foregoing use, and/or conserving, all of which change the peak to off-peak usage ratio, but by different amounts, and which lead to different results in terms of the nominal change in peak usage. In Patrick's formulation, conservation behavior is defined as a special case of foregoing consumption characterized by an equal proportional reduction in peak and off-peak usage within a day.

Load shifting and foregoing consumption comport with reported customer behaviors and response to high prices. For example, in order to shift load, some customers re-arrange their production schedule so that peak electricity usage can be reduced and compensated for by increased off-peak use. Foregone consumption represents short-term sacrifices in terms of the business environment without a commensurate change in the business activity (e.g., reduced amenity level).

[13] In effect customers utilize a slack input that allows the firm's output to continue unabated while lowering electricity consumption, at least for short periods.

However, the conservation case is more difficult to square with rational behavior. Why would a customer that reduces peak usage by foregoing in order to realize bill savings in response to high prices, also reduce their off-peak usage that is subject to much lower prices as part of their short-term behavioral response? Such a response would appear to be at odds with rational economic behavior. But, there are several plausible explanations. The most compelling explanation is that customers encounter indivisibilities, such as having to shut down equipment or processes for a longer period, such as an entire shift, in their efforts to reduce discretionary usage during high-priced peak hours. A second possibility is that this type of customer behavior might reflect a "good citizen" ethic. Customers may reduce their peak usage because high prices are often associated with conditions where system reliability is jeopardized and a public appeal may have been issued to customers urging them to lower consumption (conserve). These customers may then turn off devices for hours that extend well beyond the period of high prices (i.e., the peak period). The consequence of these actions is that the customer's total daily load is reduced proportional to the peak reduction. A third explanation is that conservation may actually reflect the combined effect of a customer taking several actions that involve discretionary curtailments and/or load shifts. These actions cumulatively result in the amount of load shifted such that the change in peak and off-peak usage is proportional (as shown in Panel C).

Following Patrick, to separate shifting affects from those due to foregone consumption, we estimate the following regression equation in the LRC model:

(14) $\{\%\Delta Q_T\} = a + \sum_m (F_m) D_m + \beta_q \{\%\Delta q_p\} + u$,

where:
$\%\Delta Q_T$ = % change in daily kWh usage relative to the daily CBL,
$\%\Delta q_p$ = % change in daily peak period usage relative to the CBL during the peak,
F_m represents firm characteristic variables
D_m are firm dummy variables
a and β_q are parameters to be estimated,
u is an error term, and
CBL is the customer baseline load, which represents the customer's typical usage on days when peak and off-peak prices are relatively low.

This LRC model can be applied to individual customers, to customer aggregates that represent segments or communities of interest, or to the population as a whole. Because the CES model was estimated for customer aggregates (e.g., industrial, commercial, government and education), this relationship is estimated for the same aggregates in the LRC model to support developing a simulation model to forecast nominal peak and off-peak load changes, as described below.

To interpret the coefficients of the LRC model, it is important to remember that as the price of on-peak electricity rises (ceteris paribus), electricity becomes a more expensive input for customers, and there is a tendency for the overall demand for electricity to fall, as customers in effect forego usage based on its cost. However, to hold output constant, customers also have an incentive for some load to be shifted from the peak to the off-peak period. The parameter, β_q, associated with the variable $\%\Delta q_p$ in (14) can be interpreted in a way that isolates these two effects.

The variable $\%\Delta q_p$ measures the combined substitution and conservation effect during the peak period, while its effect, β_q, indicates the proportion of peak conservation behavior that is consistently observed across the entire daily demand cycle. That is, β_q is the proportion of the reduction in peak demand that is due to overall daily energy conservation. Consequently, only that proportion of peak load reduction equal in percentage terms to the percentage downward shift in total daily load due to the higher cost of electricity is counted as conservation. This is as it should be because electricity conserved on a particular day involves foregoing consumption proportionally in both the peak and the off-peak period.[14]

While the coefficient β_q accounts for the proportion of load reduction on peak that is equal to the overall downward shift in daily load, $(1 - \beta_q)$ is the proportion of peak load shifted to off-peak periods. It captures the non-parallel change in the peak to off-peak load shape that is due to the fact that peak price is higher relative to off-peak price, which leads customers to substitute on-peak electricity for off-peak electricity. These measures are exact, provided there is no output effect. By including the D_m variables (e.g., dummy variables representing firm characteristics) as slope shifters, we can test for differences in conservation and load shifting behavior for sub-groups of firms. This allows us to identify characteristics that help us explain which type of behavior is likely to be exhibited.

Given this interpretation of β_q, one would expect that $0 < \beta_q \leq 1$.[15] If β_q were to take on an extreme value of zero, then as peak demand is reduced relative to the customer's CBL in response to higher prices, the entire change would be due to shifting usage from peak to off-peak periods. Conversely, if $\beta_q = 1$, then the identical proportional reduction in peak period usage is also observed in the off-peak period (i.e., a conservation behavioral response or action as defined by Patrick; there is foregone peak load, but none is shifted to the off- peak period). Values between the extremes are somewhat more difficult to interpret. Technically speaking, $\beta_q = 0.5$ implies half of the proportion of load conserved during the peak period is equal to the proportion of load conserved across the entire day. As described previously, several different types of behavior could cause this to happen.[16]

[14] We still do not know from this analysis whether the electricity conserved on the day is never consumed or is consumed on another day. Such an analysis is beyond the scope of this research.

[15] Values outside this range simply reflect unusual load profiles, i.e. extreme cases.

[16] First, if the peak load and off-peak load are identical but the load reduction is only observed in the peak-period, then 50% of the peak load reduction is counted as a daily reduction in load. To illustrate, let x equal the reduction in demand on peak. If Y is the identical in level of peak and off-peak load, then (x/Y) represents the proportional reduction in peak demand, while (x/2Y) = (1/2) * (x/Y) represents the proportion of daily load reduction. Only half of the peak load reduction is considered conserved since the curtailment was not consistently maintained throughout the day. Alternatively, it could be that off-peak load is three times that of on-peak load. If the reduction in load on-peak is x but off-peak load is also reduced by x, then the proportion of load reduced on peak remains (x\Y) while the proportion of load

Table E-1 shows four examples that illustrate the LRC model's assumptions, along with the interpretation of these results. In these four examples, assume that a group of customers reduce their peak usage by 20 MWh (or 50%) relative to their expected peak usage under "baseline" conditions. In Case 1, these customers increase their off-peak load by 20 MWh, which exactly offsets their peak load reduction and results in no net change in load across the day. Such a consumption pattern is characterized as complete substitution or load shifting (Beta = 0). Case 2 represents the opposite extreme in which customers reduce peak and off-peak load within the day by 50%, which causes the daily load to be half the daily CBL. Since the proportional load reduction is identical in both time periods, the model identifies this behavior as conservation (Beta = 1.0).

Table E-1. Shifting vs. Conservation Model Example

Cases	Peak Load	Peak CBL	Peak Load	Peak CBL	Daily Load	Daily CBL	%Diff-Peak	Off Peak	%Diff Daily	Implied Beta	Amt. Cons.	Amt. Shifted
1	20	40	70	50	90	90	-0.50	0.40	0.00	0.00	0.0	20.0
2	20	40	25	50	45	90	-0.50	-0.50	-0.50	1.00	20.0	0.0
3	20	40	50	50	70	90	-0.50	0.00	-0.22	0.44	8.9	11.1
4	20	40	40	50	60	90	-0.50	-0.20	-0.33	0.67	13.3	6.7

Case 3 assumes that customers reduce their expected peak load by 50% but do not alter behavior in the off-peak period. These types of discretionary load curtailments result in a mitigating effect on the daily load reduction (50% for the peak period vs. 22% for the entire day). That portion of peak CBL that is equal to the proportional reduction in load across the entire day is counted as conservation (e.g. 22% * 40 MWh = 8.9 MWh). Thus, of the total 20 MWh peak load reduction, about 8.9 MWh is identified as conservation because the proportional reduction in the peak period is not consistently and universally maintained across the day. The remaining 11.1 MWh is considered shifted from peak to off-peak periods. In the fourth case, customers reduce load in both the peak and off-peak periods but in different proportions (compared to case 2). Once again, the effect is that the daily deviation from the CBL is lower than in the peak period because off-peak curtailments were lower as a proportion of CBL. In case 4, about 13.3 MWh of the 20 MWh peak load curtailment is considered conservation while the remainder is identified as load shifting.

Estimating Aggregate Demand Response

The CES and LRC models can be utilized to simulate the amount of load curtailed at different prices by customers during the peak period. In effect, it is possible to construct a supply curve of customer demand response based on the estimated elasticity values. These estimates of demand response are of interest to policymakers, utilities and ISOs. For example, it would be helpful for NMPC to forecast the expected level of load

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reduced in the day is [(x + x) / (Y + 3Y)] = (2x/4Y) = (x/2Y) = (1/2) * (x/Y). Once again β_q is estimated to be 0.5 but for an entirely different type of behavior.

reduction from SC-3A customers if prices are high as the utility decides how to adjust load purchases in the NYISO Day-Ahead Market. This information may also help the NYISO, who must secure the bulk power system against possible contingencies. Regulators interested in promoting demand-side price-responsiveness could also benefit by using the estimates to set reasonable goals for RTP (or DR) programs.

By definition, the elasticity of substitution is a percentage change in the peak to off-peak ratio of demand for a 1% change in the off-peak to peak price ratio. In order to assess what happens to the ratio of peak to off-peak load as prices change, the elasticity estimate can be rearranged to produce the expected ratio of peak to off-peak electricity as follows:

$$(15)\ \sigma = \{ [(k_p/k_o) - (k^*_p/k^*_o)] / (k^*_p/k^*_o) \} / \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \}$$

$$(16\ \{ [(k_p/k_o) - (k^*_p/k^*_o)] / (k^*_p/k^*_o) \} = \sigma \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \}$$

$$(17)\ [(k_p/k_o) - (k^*_p/k^*_o)] \} = \sigma (k^*_p/k^*_o) \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \}$$

$$(18)\ (k_p/k_o) = (k^*_p/k^*_o) \sigma \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o),$$

where k_p and k_o represent actual peak and off-peak electricity consumption at the observed peak and off-peak price of p_p and p_o respectively, and k^*_p and k^*_o represent a reference CBL peak and off-peak electricity consumption at a reference peak and off-peak price of p^*_p and p^*_o respectively.

In order to estimate the actual on-peak and off-peak load expected to be induced by customers' price response, we must make an assumption regarding the nature of the observed changes in electricity consumption. Specifically, we assume that total load in the day remains constant regardless of price changes.[17] If total load is unchanged, then k_o (off-peak load) can be re-specified using k_p, k^*_p , and k^*_o as follows to get a single expression for actual on-peak electricity consumption (k_p):

$$(19)\ [k_p/ (k^*_p + k^*_o - k_p)] = (k^*_p/k^*_o) \sigma \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)$$

$$(20)\ k_p = (k^*_p + k^*_o - k_p) \{ (k^*_p/k^*_o) \sigma \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\}$$

$$(21)\ k_p = (k^*_p + k^*_o) \{(k^*_p/k^*_o) \sigma \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} / [\{ (k^*_p/k^*_o) \sigma \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} + 1]$$

To estimate k_p, the peak load that would result from a price change from p^*_o and p^*_p to p_o and p_p, requires specifying the reference peak and off-peak loads under "normal" conditions and prices (which we define as the average prices during the periods used to calculate the CBL). We use the definition of CBL in the LRC model, along with the substitution elasticities estimated in the final CES model in order to predict the amount of

[17] This assumption would be generally consistent with the CES models' assumption of a constant energy aggregate, but would not require one to solve for the energy aggregate itself.

peak load that would be curtailed in response to a change in the ratio of off-peak to peak prices. Because the CBL was estimated for days less than $0.075/kWh, the demonstration simulation exercise begins with this price and increases it by $0.025/kWh increments until the market cap of $1.00/kWh is reached.[18] At each price point, the level of peak demand is calculated and the difference between this estimate and the CBL represents the amount of demand response that would be forthcoming at that price.

In terms of our specific application, we constructed the aggregate demand response supply curve by utilizing the elasticity estimates from the "final" CES model results for 32 customers and applying these elasticity estimates to the 141 customers in the SC-3A target population. However, in the "final" CES model, we include several categorical variables (drawn from the customer survey) that are not known for the entire SC-3A target population. Thus, in order to extrapolate the elasticity results from the 32 customers to the 141 customers in the SC-3A target population, we grouped the "final" elasticity results in a manner that is consistent with the groupings available for the target population of customers.[19] Thus, we assigned each customer in the target population to one of these categories and then designated the elasticity estimate from the final CES model results for that category in an attempt to characterize their expected price responsiveness.

One drawback of this simulation model is the effect of the constant daily load assumption on the estimated peak load reduction. As previously noted, several customers indicated they undertake simple curtailment measures that do not require the firm to increase use in another period. This would cause daily load to decrease while potentially causing off-peak load to instead remain constant. By requiring daily load to be fixed, the CES model elasticity estimates under-estimate the customer's peak-load reduction since it does not account for the lower overall daily load that would have occurred. If instead off-peak load is held constant in the simulation model, the load curtailment on-peak for customers who execute these simple behaviors is correctly predicted, but will bias upwards those customers who perfectly shift their consumption from peak to off-peak periods. Another adjustment method must be found to consistently predict as accurately as possible the peak load reductions of customers who exhibit these different types of behavior.

Adjusting Aggregate Load Response for the Conservation Behavior Effect

As demonstrated above, to predict the nominal kWh reduction in peak and off-peak given a specified change in the ratio of peak to off-peak prices, it is necessary to adjust the substitution elasticity to account for the conservation behavior effect. Estimating the LRC model, adapted from Patrick (1990), provides an estimate of the conservation effect from daily deviations from CBL as a proportion of peak period deviations.

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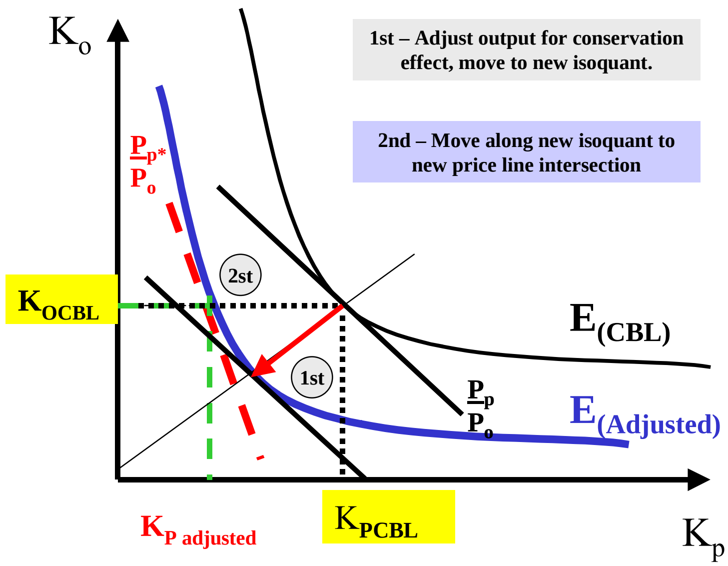
[18] In some cases, the average price during the peak period on "CBL" days could be less than $0.075/kWh, in which case there would be an expected curtailment, however small, at even this low price.
[19] We summarized elasticity estimates for the 32 customers included in the "final" model results segmented by market segment (e.g., industrial, commercial, government/education) and participation status in NYISO DR programs, because this information was also available for each customer in the target population.

Panel D illustrates the process. First, the estimate of the conservation effect, β_q, is used to adjust the firm's typical (CBL) load downward to a new isoquant. Then, the substitution elasticity is applied to the adjusted CBL to derive estimates for the new peak and off-peak kWh levels consistent with the new price ratio. The difference between the original CBL and the new estimated load is the total adjustment due to the price change.

Panel D



Peak Electricity Usage

To operationally apply this methodology requires knowing how to adjust the CBL for the expected conservation effect. We define the CBL as the level of usage that the customer would have used absent the price change. To make this adjustment, it is necessary to know either the expected level of conservation in the peak period or the expected level of conservation across the day. Since neither is known definitively, the originally simulated value for peak load (k_p), as estimated using (21),

$$(21)\ k_p = (k^*_p + k^*_o)\ \{(k^*_p/k^*_o)\ \sigma\ \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} / [\{ (k^*_p/k^*_o)\ \sigma\ \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} + 1]$$

and the estimated conservation coefficient (β), from (14) above, can be used to calculate an estimate of the percentage change in total load as follows:

$$(22)\ (k^{**}_T - k^*_T)/(k^*_T) = \alpha + \beta\ [(k_p - k^*_p)/(k^*_p)]$$

If the intercept term, α, is assumed to be zero, then 100% of daily deviations from CBL are attributable to "conservation" behavior, even though there may be peak and off-peak changes that result from combinations of shifting and conservation efforts. So if the overall daily load is reduced, the peak and off-peak load must also be adjusted downwards by this same proportional amount to account for the effects of conservation.

This is accomplished by calculating an "adjusted" peak and off-peak CBL (k^{**}_p and k^{**}_o respectively) as follows:

$$(23)\ k^{**}_p = k^{*}_p\ [(k^{**}_T - k^{*}_T)/(k^{*}_T)\ ]$$

$$(24)\ k^{**}_o = k^{*}_o\ [(k^{**}_T - k^{*}_T)/(k^{*}_T)\ ]$$

These "adjusted" CBL values are assumed to represent a point on a lower isoquant, since the total energy aggregate has been reduced while total firm output has been maintained. The difference between the original CBL and the "adjusted" CBL represents the amount of load conserved. The original CBL values in (21) are replaced with the "adjusted" CBL values from equations (23) and (24) to simulate what the "corrected" estimate of peak and off-peak load for the given change in prices and estimated elasticity of substitution:

$$(25)\ k^N_p = (k^{**}_p + k^{**}_o)\ \{(k^{**}_p/k^{**}_o)\ \sigma\ \{\ [\ (p_o\ /p_p) - (p^{*}_o/p^{*}_p)\ ]\ /\ (p^{*}_o/p^{*}_p)\ \} + (k^{**}_p/k^{**}_o)\}\ /\ [\ \{\ (k^{**}_p/k^{**}_o)\ \sigma\ \{\ [\ (p_o\ /p_p) - (p^{*}_o/p^{*}_p)\ ]\ /\ (p^{*}_o/p^{*}_p)\ \} + (k^{**}_p/k^{**}_o)\} + 1\ ]$$

$$(26)\ k^N_o = k^{**}_T - k^N_p$$

Together, an estimate of the substitution elasticity and an estimate of the conservation effect provide the means for estimating the changes in energy use on both peak and off-peak periods. They also provide the basis for simulating the impact of price changes on peak consumption (which is the focus of most demand response programs) and off-peak consumption, a collateral impact that is important for fully characterizing the program impacts.[20]

Final CES Model Results

In the *Final* CES model, we tested a number of variables derived from customer survey responses. Our goal was to see if additional, in-depth information about customer circumstances would provide for a more robust characterization of electricity usage, and identify important drivers to price response.

Model Specification

Many of the survey-derived variables proved to be insignificant in explaining differences in groups and were omitted.[21] However, several variables provided important explanatory information and were included:

[20] The revenue impact of demand response has been an issue in program design. For example, the PJM real-time pricing program deducts from the participant's curtailment payment an amount that represents the T&D revenue the wires company would have received, but for the curtailment. However, there is no attempt to ascertain if the customer's response was discretionary curtailment or load shifting. If the response is the latter, this transfer amounts to a windfall rents to LSE.

[21] In some cases the variables provided redundant measures to factors already included. In others, the hypothesized effect was not forthcoming in terms of a parameter estimate that was statistically significant.

- *Time of Peak Usage*: The information that customers provided about when their load peaked was used to design an alternative indicator of the ability to shift; whether peak usage occurred between noon and 5 pm, or some other time of the day.
- *Relative importance of electricity costs*: Survey respondents' assessment of their electricity costs as a percent of annual operating costs was also assigned to a variable. Customers were sorted according to whether they reported their electricity costs were equal to or greater than 10% or less than 10% of operating costs.
- *Investments in DR enabling technologies*: We posited that customers that had invested in various DR enabling technologies that helps them shift load would be more price responsive. A dummy variable was constructed to reflect whether the customer had made a technology investment after the start of the RTP-based SC-3A service in 1998 and another dummy variable for similar investments prior to 1998.[22]
- *Participation in NYISO EDRP*: To isolate the impact of these additional inducements to curtail from NYISO programs, the dummy specification also distinguished between EDRP event days, and other "non-event" days, thereby allowing for the elasticity of EDRP participants to vary according to whether the customer faced SC-3A prices or was provided an additional inducement ($.50/kWh) to curtail. Our hypothesis was that the extra inducement would increase price response, over what the customer would otherwise accomplish based on SC-3A prices.

Hourly price and load from 32 customers were used to estimate the Final CES models.[23] This reduction in sample size resulted from the pattern of survey responses; only those customers that answered *all* the relevant questions could be analyzed.[24]

Model Parameter Estimates

Table E-2 summarizes the model estimates. The high F-Test values support rejecting the hypothesis that all the parameters values are in fact zero, and indication of the robustness of the specification. Overall the model explained about 25% (R^2) of the variation in customer's peak usage ratio over the three summer periods. Because there are only about 25% as many customers in this model as were used in the initial specification, a lower R^2 is to be expected.

[22] In creating the dummy variable for investments in DR enabling technologies, customers that invested in process/building automation systems, control devices on specific equipment or processes, or peak load management control devices were coded as "1"; other responses were coded as "0" (see question 31 in survey)

[23] We used dummy variable slope shifters to distinguish differences in elasticity among the three business sectors (Government/education, Industrial, Commercial) thereby allowing for an individual substitution elasticity estimate for each sector and to reflect enrollment in NYISO DR programs.

[24] In order to include answers to a survey question in the estimated demand equations, survey respondents had to provide a definitive answer: either a "Yes" or a "No". A choice to not respond to the question, which was an option on every question, provides no information concerning classification of the explanatory variable and thus, that customer was omitted from the final CES model sample.

Table E-2. Final CES Demand Model Parameter Estimates

Variable	Short Peak		Medium Peak		Long Peak	
Log Inverse Price Ratio	0.03		-0.02		-0.02	
Slope Shifter Variables - the parameters values are add to the intercept to derive the corresponding substitution elasticity estimate						
Business Sector						
Gov't / Education	0.63	*	0.58	*	0.52	*
Commercial	0.34	*	0.30	*	0.28	*
Industrial	0.30	*	0.29	*	0.26	**
Other Factors						
Peak Usage Noon-5 PM	-0.23	*	-0.21	*	-0.19	*
Electricity Cost > 10% Op Cost	-0.10	**	-0.08	**	-0.08	**
Investment made prior to RTP	-0.18	*	-0.13	*	-0.11	**
Investment made while on RTP	-0.07		-0.05		-0.04	
Temp > 70	0.01		0.02		0.02	
Year=2001	0.00		-0.01		0.00	
EDRP Non-Event Days						
Gov't/Ed EDRP Participant	-0.05		-0.08	**	-0.10	*
Commercial EDRP Participant	-0.13	***	-0.10		-0.08	
Industrial EDRP Participant	-0.30	*	-0.25	*	-0.21	*
Other EDRP Participant	-0.16	***	-0.17	**	-0.19	**
EDRP Event Days						
Gov't/Ed EDRP Participant	-0.07		-0.09		-0.07	
Commercial EDRP Participant	-0.16		-0.13		-0.12	
Industrial EDRP Participant	0.47	*	0.38	*	0.37	*
Other EDRP Participant	0.43	*	0.44	*	0.43	*
Other NYISO PRL Participation						
NYISO DADRP Participant	0.52	*	0.43	*	0.33	*
NYISO SCR Participant	0.18	**	0.18	**	0.16	**
R-Squared	0.23		0.25		0.27	
F-Test of Global Significance	34.04	*	37.20*		41.72	*

Short Peak = 2:00-5:00, Medium Peak = 1:00-5:00, Long Peak = Noon - 5:00
*** = Significant at 1% level**
**** = Significant at 5% level**
***** = Significant at 10% level**
Values less than 0.005 appear as 0.00 due to rounding
32 Customers included

The estimated parameters for the Final CES model are presented for the three alternative peak specifications, Short (2-5:00 p.m.), Medium (1-5:00 p.m.), and Long (noon-5:00 p.m.) of what constitutes the daily peak period. In general, the parameter estimates get smaller as the peak period definition gets longer. This is to be expected. A longer peak means that shifting to avoid the prices in that period requires a greater effort. The Long peak is comprised of the entire afternoon, so shifting load to off peak in effect requires rearranging the entire day's activities. The Short peak, in contrast, leaves more room to maneuver, since the early afternoon hours are available (off-peak) to make up for the peak load reduction. In our discussion, we will refer primarily to parameter estimates for the Long peak period (noon – 5 pm), as it had the best fit results for the CES model.

Importantly, three of the variables derived from the survey data are significant and have a substantial impact of the elasticity estimates. These results indicate that participation in other NYISO DR programs (DADRP and ICAP/SCR) enhances price response (the base elasticities are increased by 0.33 and 0.16 respectively). This is not surprising, since both programs provide additional financial incentives to curtail and assess penalties for non-compliance.[25]

Customers that report peak usage between noon and 5:00 p.m. and those with high electricity intensity are less responsive than other customers, all else equal. Specifically, customers that peak during mid-day or indicate electricity costs exceed 10% of total costs would reduce their substitution elasticity by 0.19 and 0.08 respectively. This is consistent with the notion that it is harder for customers to curtail when critical business activity and electric use coincide with times of high prices.[26] However, note that subtracting these amounts from the base elasticities above for the three business sectors still leaves positive elasticity values.

However, the technology investment results are counter-intuitive. The negative marginal elasticities indicate that investing in enabling DR technologies actually decreases price responsiveness. This effect is much more pronounced for the DR investments made before 1998. For investments made after 1998, the negative impact on elasticity is small, but we would expect these DR-oriented investments to facilitate price response. It may be that customers have received peak load management devices or information systems from NMPC or through NYSERDA public benefit programs, but have not taken full advantage of their capabilities. Many customers reported that they made EIS investments in an attempt to better understand the overall load profile at their facility, not to expressly improve their ability to be price-responsive. Information from EIS and EMCS were often used to reduce overall electricity consumption as well as reduce usage during peak periods.[27] Another possibility is that the equipment was installed relatively recently so

[25] ICAP/SCR allows customers to sell their curtailment capability to a load-serving entity to meet its installed capacity requirement. Customers receive an energy payment for their load reduction if called. Failure to comply with curtailment events can result in financial penalties and a derating of the curtailable load the customer can sell in the future.

[26] However, other studies of industrial response to RTP have found the opposite result: that customers with more electricity-intensive production tend to be more, not less, responsive (Christensen Associates, 2000).

[27] In addition, the decision to invest in enabling DR technologies is assumed to be exogenous (i.e., independent) of price-responsiveness in our model specification. Many believe that customers invest in technology because they already are savvy about their electricity demands. To mitigate the possible effects of this assumption, a choice model could be developed to predict investment in energy management equipment, the results of which would be included in the model as a truly exogenous explanatory variable. Time and resources did not permit such activities in this phase of the analysis, but is a subject for continuing research in this area.

that it was not available during the period covered by our demand modeling.[28] Finally, investments in DR-enabling technologies may be correlated with other factors that reduce price response but are not accounted for in the model. Further research is needed to more clearly specify the impact of technology on price response. The last two factors, temperatures over 70 degrees and the year 2001 (characterized by much higher price volatility) have negligible incremental impacts on the elasticity.[29]

The substitution elasticities derived from the Final CES model for the Long peak period are presented in **Table E-3**. The average load-weighted substitution elasticity over all business categories, customer circumstances, and other influences was 0.14, which is double that derived from the Initial CES model.

Table E-3. Final Model Elasticity Estimates for Long Peak

		Gov't/Ed	Commercial	Industrial	Other
1	Just SC-3A*	0.50	0.26	0.24	-0.02
2	SC-3A/EDRP/ Non Event Days*	0.40	0.18	0.03	-0.21
3	SC-3A/EDRP/ Event Days	0.34	0.06	0.40	0.22
	Additional Factors (add to cell values above)				
4	DADRP Participation			0.33	
5	ICAP/SCR Participation			0.16	
6	Peak Usage 12 Noon - 5 PM			-0.19	
7	Electricity Costs over 10%			-0.08	
8	Investment Prior to 1998			-0.11	
9	Investment After 1998			-0.04	
10	Temp > 70			0.02	
11	Year = 2001			0.00	

Moreover, the Final model specification reveals greater variation among the average elasticity values for the three customer groups, to wit: Government/education (0.30), Industrial (0.11), and Commercial (0.0). The industrial value is in the range of what studies of other RTP programs have produced (Schwarz et. al., 2002, Herriges et. al. 1993). The estimated elasticity for the Government/education group is surprising, as it exceeds that of industrial customers that are generally considered to be the best equipped to respond to prices.[30]

[28] NYSERDA implemented programs beginning in 2001 that provided incentives to customers to install technologies that would assist them in responding to the NYISO demand response programs. However, many projects were not operational until the summer of 2002 so the cumulative impact is not reflected in the modeled data.

[29] Because hot days are often associated with high day-ahead prices and EDRP and ICAP/SCR events, isolating a separate heat effect is difficult.

[30] Schwarz et. al. (2002) also found relatively high elasticity for a comparable group.

The unbundled estimated substitution elasticity results are presented by business sector (the columns in Table E-2) in a progressive order, beginning with the elasticities for Just SC-3A customers (Row 1), representing customers on SC-3A tariff but not enrolled in a NYISO DR program. The Just SC-3A elasticity value for the Government/education (0.50) sector is over twice that of the Commercial (0.26) and Industrial (0.24) sectors.[31]

Under most circumstances, government/educational customers are significantly more price responsive than other customer groups. This is in stark contrast to the findings of previous RTP studies in which price response of industrial customers (as measured by elasticity values) is typically much higher than other customers. However, on EDRP event days, government/education EDRP participants are ~30% less price elastic than non-participant government/education customers. This may indicate that these customers have already curtailed or shifted load in response to SC-3A day-ahead prices when the NYISO calls an EDRP event, leaving limited opportunities to shed additional load, even at the higher EDRP inducement price. This explanation is based on the notion that some customers have a maximum amount of curtailable load.[32]

Industrial customers enrolled in EDRP, on the other hand, show dramatically higher price response during EDRP events compared to industrial customer response to SC-3A prices alone: 0.40 substitution elasticity during EDRP events vs. 0.24 for customers not enrolled in EDRP and 0.03 for non-event days for industrial customers enrolled in EDRP. For these customers, the EDRP program appears to entice price response that SC-3A prices do not.

Rows 4 and 5 indicate that participation in other NYISO DR programs further enhances price response. The incremental elasticity values are 0.33 and 0.16 for DADRP and ICAP/SCR, respectively (for each business sector, these values are additive to those from rows 1-3, if the customer is a program participant). The ICAP/SCR result is expected, as these customers face potentially significant penalties for failure to comply with the curtailment order, and in addition they receive an energy payment for their load reduction.[33] The DADRP estimate suggests the prospect of getting paid to curtail boosts customer response over that which would be forthcoming from SC-3A prices alone.[34]

[31] Customers in the Other category represent an aggregation comprised of several customers of unique identity and circumstances that require masking. Moreover, their elasticity estimates are generally insignificant and have the wrong sign.

[32] Typically, EDRP events are preceded by high day-ahead market prices, which are the basis for SC-3A prices. The model we employed assumes that elasticity is constant at all prices; thus computed elasticities may be lower if prices continue to increase after customers have reached their maximum load-shedding capability than they would be for the same load response at lower prices. Further research using demand models that do not impose this constant-elasticity constraint, augmented by customer interviews on their curtailment potential, may help resolve this apparent paradox.

[33] ICAP/SCR allows customers to sell their curtailment capability to a load-serving entity to meet its installed capacity requirement. Failure to comply with curtailment events can result in financial penalties and a derating of the curtailable load the customer can sell in the future.

[34] DADRP allows customer to bid curtailments into the NYISO day-ahead market, and if scheduled, receive the day-ahead market price if they curtail as scheduled the next day. In effect, they get paid to respond to prices that are themselves an inducement to respond, which some argue is a double payment.

Rows 6-11 in Table E provide elasticity estimates associated with other influences. Elasticities are decremented for customers (of all sectors) that report having their peak usage between noon and 5:00 p.m. (by 0.19), electricity costs that exceed 10% of total costs (by 0.18), and invested in enabling technology before and after 1998 (by 0.11 and 0.04 respectively). The first two results seem sensible: all other things equal, it is harder for customers to curtail when business activity and electric use coincide with times of high prices. The technology investment (a decrement to the elasticity) results seems counterintuitive, and may represent a correlation with such reported investment behavior and some other deleterious factor to price response. This is another anomalous result that merits further research to resolve. The last two factors, temperatures over 70 degrees and the year 2001 (characterized by much higher price volatility) have negligible incremental impacts on the elasticity.[35]

In summary, the estimated average business class elasticities belie the diversity of response among customers in the same business classifications. Participation in NYISO EDRP program has a profound correspondence with customer response; in some cases associated with an augmentation of the price response induced by SC-3A rates (e.g., Industrial customers). In addition, there is strong complementarity between the ICAP/SCR program and SC-3A. These findings lend support to proponents of ISO DR programs in conjunction with RTP-type rate designs, even if RTP participation is the utility standard offer tariff.

Attachment A: The Generalized Leontief Specification

The CES model is commonly used to estimate the demand for electricity because it provides a consistent representation of cost-minimizing behavior and lends itself to straightforward statistical estimation. However, its implicit assumption about the nature of substitution, that it is constant regardless of relative prices, is restrictive, particularly in light of our customer survey and demand modeling results.[36]

An alternative specification of electricity demand is based on the Indirect Generalized Leontief (GL) Cost Function. We discuss the GL model specification in this attachment as it constitutes a logical next step in evaluating SC-3A customer response. To begin, as before, we specify a firm's production function that is separable in electricity inputs as:

(1a) $Q = F(x_1, x_2,\ldots,x_n , q(k_1,\ldots, k_n))$,

However, these results suggest that customers treat the two situations differently when it comes to adjusting usage.

[35] Because hot days are often associated with high day-ahead prices and EDRP and ICAP/SRC events, isolating a separate heat effect is difficult.

[36] We found that some customers that participate in the NYISO EDRP program, which offers a floor price of $0.50/kWh for curtailments, are much more price-elastic than other customers that are not exposed to these high prices in their SC-3A rates.

where Q is output, x_i are inputs other than electricity, and $k_i, \ldots, k_n$ are amounts of electricity used during periods i through n, respectively. Because production is assumed to be separable in electricity inputs, we can specify the function F as above, where the electricity inputs can be combined according to an aggregator function q. This is essentially being able to specify a sub-function within F. Any combination of $k_1, \ldots, k_n$ that yields the same value for q is equally productive in producing Q. It is the nature of this sub-function that determines the substitutability of electricity among different periods of the day.

Appealing to duality theory (Shephard, 1970), we can also, in theory, specify the indirect cost functions associated with both the production function Q and the sub-function q above.[37] Because of the assumption that the function is separable in electricity inputs, we are only concerned with the indirect cost function associated with the electricity aggregate's sub-function. From that sub-function, we can derive expressions for the elasticity of substitution among electricity use during different times of the day.

If we assume that the underlying aggregator function for q is linear homogenous in the electricity inputs (k_i) and that the indirect cost function C is a flexible generalized Leontief function, then we have for n daily time periods (for i, j = 1,…,n):[38]

(2a) $C = q\ \{\sum_i \sum_j d_{ij}\ (p_i\ p_j)^{1/2}\}$;

This function is linear homogenous in all prices, which is a requirement for a well behaved indirect cost function. That is, if all prices are changed in the same proportion, then C changes in the same proportion as well. We also require that $d_{ij} = d_{ji}$, for symmetry.

From Shepherd (1970), we know that optimal factor demands can be determined by differentiating (2) with respect to each price (i = 1, … ,n):

(3a) $\partial C/\partial p_i = k_i = q\ [\sum_j d_{ij}\ (p_j / p_i)^{1/2}]$.

One purpose of flexible cost functions is to facilitate the estimation of the Allen (1938) partial elasticities of input substitution, which, for a cost function (21), are equal to:[39]

[37] This involves solving the first-order conditions to the constrained optimization problem for minimizing the cost of producing a given output for the factor demands and substituting them back into the direct cost function. This procedure allows one to write the indirect cost-minimizing cost function in terms of output and input prices only.

[38] Diewert (1974) shows that if the generalized Leontief function (or any cost function) can be decomposed in this form, then the underlying aggregator function for q reflects a constant returns to scale technology.

[39] As discussed originally by Allen (1938, pp. 508-09), the partial elasticity measures the degree to which the demand for factor j changes as the price of factor i changes. If $\sigma_{ij} > 0$, and the price of factor i increases, then the use of factor j increases, thereby taking part in the replacement of factor i in production. The two factors are said to be *competitive*. If, on the other hand, $\sigma_{ij} < 0$, the two factors are *complements*, and as the price of one of them rises, the demand for both falls. Competitiveness between factors is, on the whole, more general than complementarity. One factor cannot be complementary with all others. In the two input case, direct elasticity of substitution (which measures the percentage change in factor intensities as the inverse price ratio changes by one percent) is equal to the Allen partial elasticity of substitution.

(4a) $\sigma_{ij} = C_{ij} / [C_i C_j]$,

where the subscripts refer to the first and second order partial derivatives of C with respect to inputs i and j. Evaluating equation (4a) for the GL cost function given in equation (3a), we have:

(5a) $\sigma_{ij} = ½ [C\, d_{ij} (p_i\, p_j)^{-1/2}] / [q\, a_i\, a_j]$,

for all i and j, but $i \neq j$ and $a_i = k_i / q$. In contrast to the CES model, the elasticity of substitution for the GL model varies from observation to observation. In this case, the Allen partial elasticity of substitution varies with price ratios, the energy aggregate and the cost minimizing input levels. Further, for the Allen own partial elasticities of substitution, we have (for all i):

(6a) $\sigma_{ii} = -½ [C \sum_{j\neq i} d_{ij} (p_j^{-1/2}\, p_i^{-3/2})] / [q\, a_i^2]$.

Normally, to estimate the parameters of this cost function, one need only assume an additive error structure associated with the input demand equations (3a), and then estimate them as a system of equations where there are across-equation restrictions to insure symmetry of the parameters. This is accomplished most conveniently by dividing each equation by q (Berndt, 1991). That is, one can simply estimate for all i:

(7a) $a_i = k_i / q = [\sum_j d_{ij} (p_j / p_i)^{½}]$.

When j = i, we have $(p_j / p_i) = 1$, and d_{ii} is a constant in the equation for a_i. In this formulation, one can implicitly restrict the coefficients to be symmetric by always writing the subscripts in the same order.

Unfortunately, because q in this case is the energy aggregate and cannot be observed directly, it is impossible to employ this strategy. However, using full information maximum likelihood (FIML) methods within PROC MODEL in SAS, one can estimate the parameters from equations for the ratios of the a_i. That is, we can estimate (for all $i \neq m$):

(8a) $k_i / k_m = [\sum_j d_{ij} (p_j / p_i)^{½}] / [\sum_j d_{mj} (p_j / p_m)^{½}]$.

Within PROC MODEL one can also impose the symmetry restrictions on d_{ij}, and force the adding up restrictions to ensure the function is well behaved globally, $\sum_i \sum_j d_{ij} = 1$.

In this form, the equations are extremely non-linear in the parameters, and it might be best to take the logarithms of both sides for estimation purposes:

(8a') $\ln [k_i / k_m] = \ln \{[\sum_j d_{ij} (p_j / p_i)^{½}] / [\sum_j d_{mj} (p_j / p_m)^{½}]\}$.

This strategy will not eliminate the non-linearity, but it will convert each equation into the differences between two logarithms within which there are coefficients imbedded. Whether SAS deals with that kind of non-linearity better than these quotients is an empirical question.

To evaluate the elasticities of substitution at every data point using equations (5a) and (6a), one needs estimated (or predicted) values of a_i, and C/q, the cost per unit of the electricity aggregate. One can predict a_i directly by substituting the estimated parameters into equation (7a). For convenience label these $(a_i)_{fit}$. Following Berndt (1991), one can obtain predicted values for C/q in the following way:

(9a) $(C/q)_{fit} = \sum_i P_i\ (a_i)_{fit}$.

These predicted values for each data point are then substituted into equations (5a) and (6a) to obtain elasticities of substitution.

To estimate the GL model above, one must also define exactly how the variables used in the empirical regression analysis are calculated from the data. From equation (8a'), we need to have the ratio of peak to off-peak electricity use.

Define for each weekday, t, and firm or group of firms, m:

k_{ptm} = peak kWh;
k_{0tm} = off-peak kWh;
p_{ptm} = average hourly peak price / kWh; and
p_{0tm} = average hourly off-peak price/kWh.

There are also several other variables that must be included in the model; they must be defined specifically. One set contains 0-1 or 'dummy' variables for each firm or group of firms. These variables are to account for inherent differences by firm in peak relative to off-peak energy use. These variables are defined for the m firms (m = 1,…,M): D_m = 1 if the observation is for firm m, and = 0 otherwise. It must be emphasized, however, that this is only an initial specification. By using other firm characteristics from the survey, the model can be designed to account for differences in firm-level factors directly. These factors might include, but not be limited to such things as alternative types of production processes, differences in production shifts, differences in business hours, the availability of distributed generation, the proportion of load hedged, etc.

As Schwarz *et al*. (2002) suggest, firms that have faced fixed tariffs for electricity for many years must learn how to respond to price differences between peak and off-peak periods. The efficiency should be higher the longer a firm has faced price variation. Thus, if we can obtain data on when customers were previously enrolled in some type of RTP program, we can test both the hypothesis that experience affects the overall level of peak to off-peak use, as well as the ability to shift load in response to prices (Schwartz found a modest relationship between experience and elasticity). One way to capture this effect is by defining a variable: T_{tm} = the number of months that firm m has been in the RTP program on day t. To test these separate hypotheses, this variable would have to be added as both an "intercept" shifter at this stage of the model, as well as a "slope" shifter.

Finally, the effect of daily weather on the ratio of peak to off-peak electricity use is captured through a weather index: W_{tm} = weather index for day t from the weather station nearest to firm m for which there are data.[40]

Given this set of variables, the equation to be estimated is:

(10a) $\ln [\, k_{ptm} / k_{otm} \,] = \sum_m (F_m)\, D_m + (w)\, W_{tm} + (T)\, T_{tm} + \{ \ln [\, (T_P)\, T_{tm} + (D_{pp}) + (D_{po})\, [\, p_{0tm} / p_{ptm} \,]^{1/2} - \{ \ln [\, (T_0)\, T_{tm} + (D_{oo}) + (D_{op})\, [\, p_{ptm} / p_{0tm} \,]^{1/2} \},$

where the terms in ( ) are coefficients to be estimated. We further require that $T_p=T_o$, and $D_{po} = D_{op}$, both for symmetry. We also require that $D_{oo} + D_{pp} + D_{op} + D_{po} = 1$. In this specification, it is important to note that the experience variable T_{tm} is the only firm characteristic that is included as both an intercept and a slope shifter. This was done for simplicity of exposition. The weather variable can be easily included as a slope shifter as well. The firm-level dummy variables and weather are included only as intercept shifters. By also including the firm-level dummy variables as slope shifters, one would effectively be estimating separate models for each firm. To study the effect of specific firm characteristics on electricity usage in response to price differences, this strategy would be of little use. Therefore, using other firm-level data from the survey of other sources, one can include those variables directly into the model as both intercept and slope shifters. This specification allows for direct tests of the hypotheses that certain firm-level characteristics affect price responsiveness. The specification is a decided improvement compared to accounting for firm level differences *only* through including the individual firm dummy variables. By relying only on firm-level dummy variables, one is able to measure differences in price responsiveness by firm, but we are able to say nothing about what it is about the firm that makes this so.

Attachment B: The Model with Both Within-day and Between-Day Price Response

The econometric model used to estimate both within-day and between-day price response is essentially the one used recently by Schwarz et al. (2002). They state that this model is based on a procedure in King and Shatrawka (1994), and it is a variant of the approach of Herriges et al. (1993). This model assumes a nested Constant Elasticity of Substitution (CES) functional form to characterize customer demand for electricity. Consumption within-days is weakly separable from consumption across days. This model does allow for the change in electricity use within a day in response to hourly price changes that differ from the change in electricity use between-days in response to a daily price index.[41]

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[40] Our initial specification of the weather index is based on heating and cooling degree-days constructed from mean daily temperature and dew point values for weather stations in close proximity to NMPC SC-3A customers. The construction of the index is in Attachment C.

[41] One explanation for the lack of complete correspondences between substitution elasticities and the actual, nominal peak load reductions is that customers can shift load from the peak price day to another

Since the theory underlying this structure is outlined in Appendix E, we report only the estimating equations:

(1b) $\ln (E_{dh} / E_{th}^{g*}) = \sum_t A_t - \sigma_H \ln (P_{dh} / P_{th}^{g*}) - (\sigma_D - \sigma_H) \ln (D_d / D^{g*})$

where E_{dh} is electricity use for hour h and day d and P_{dh} is the electricity price for hour h and day d. Also $\ln E_{th}^{g*} = (1/N_t) \sum_m \sum_{d\varepsilon t} \ln (E_{mdh})$ and $\ln P_{th}^{g*} = (1/N_t) \sum_m \sum_{d\varepsilon t} \ln (P_{mdh})$ are the logarithms of the geometric means over the months m of a particular season, and $\ln (D_d / D^{g*}) = (1/2) \sum_h (w_{dh} + w_{th}^{*}) \ln (P_{dh} / P_{th}^{g*})$ is a daily price index, and $w_{dh} = P_{dh} E_{dh} / \{ \sum_k P_{dk} E_{dk} \}$ is the share of electricity expenditure for hour h on day *d* and $w_{th}^{*} = [1/N_t] [\sum_m \sum_{d\varepsilon t} w_{dh}]$ is the arithmetic mean of the electricity expenditure share for hour h in all days of type t.[42] Letting $E \equiv \ln (E_{dh} / E_{th}^{g*})$; $A \equiv \sum_t A_t$; $P \equiv \ln (P_{dh} / P_{th}^{g*})$; and $D \equiv \ln (D_d / D^{g*})$, we can make the appropriate substitutions into (1c), rearrange terms and end up with the model for estimating σ_H and σ_D:

(2b) $E = A + \sigma_H (D - P) + \sigma_D (- D)$

The *a priori* expectation for the signs of both estimated coefficients is positive. As in King and Shatrawka (1994), A is a vector of binary variables that could be used to control for any influence by days of the week, or by firm. This vector of variables represent intercept shifters, but one could also include these variables easily as slope shifters so that both σ_H and σ_D could be allowed to vary by weather or firm characteristics. For example if we include a weather index, defined by day W_D and by season W_S in a manner similar to that in the text above, as slope shifters for both hourly and between-day price response, the individual response elasticities are derived as:
$\sigma_H = b_H + m_D W_D$, and $\sigma_D = b_D + m_S W_S$

After making appropriate substitutions into equation (2b) and arranging terms, we have:

(3b) $E = A + (b_H) (D - P) + (m_D) W_D (D - P) + b_D (- D) + m_S W_S (- D)$

Attachment C: Development of Weather Variables

We initially obtained historical weather data for several weather stations in NMPC's service territory from the National Climatological Data Center (NCDC) Internet site. The data set encompassed the period 01/01/2000 – 07/15/2003 and contained daily mean temperature and dew point values. These were used to calculate heating and cooling degree-days and heat indices on a daily basis.

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day. Customers may shift load between days because of conditions specific to their industrial processes or union/labor rules related to work shifts (e.g. notification requirements). If we fully accounted for both in day and between day shifts, then some of what is being classified as conservation might be explained more logically.

[42] The expression $\ln (D_d / D^{g*})$ is the daily price index formed using a Tornqvist price index. Usage in each hour, relative to the average level, is a function of relative price in that hour and the daily aggregate price index. K-S provides the Tornqvist index in footnote 3.

Variable Construction

The following formulae summarize the calculation of the variables employed in the regression models. These are based on statistics developed by the National Weather Service. Note that the derivation of the Heat Index required several intermediate steps: a) conversion of the temperature and dew point values to Celsius; b) calculation of actual and saturation vapor pressure; and c) calculation of relative humidity. This was necessary since relative humidity (RH) was not available in the NCDC data for the analysis period; and the RH is required to calculate the heat index.

Calculation of Relative Humidity

Tf = Mean temperature (FE)
Tdf = Mean dewpoint temperature (FE)
Mean temperature (CE) = Tc = 5/9 * (Tf - 32)
Mean dewpoint temperature (CE) = Tdc = 5/9 * (Tdf - 32)
Actual Vapor Pressure = E = $6.11*10.0^{(7.5*Tc / (237.7+Tc))}$
Saturation Vapor Pressure = Es = $6.11*10.0^{(7.5*Tdc / (237.7+Tdc))}$
Relative Humidity (%) = RH = (E/Es) * 100

Calculation of Degree-Day Indices

Heating degree-days (Base 65)(HDD65)
if Tf >=65, HDD65 = 0
if Tf <65, HDD65 = 65 - Tf
Cooling Degree-Days (Base 65) (CDD65)

- if Tf <=65, CDD65 = 0
- if Tf >65, CDD65 = Tf – 65

Heat Index (HI70)

if Tf <=70, HI70 = Tf
if Tf >70, HI70 = - 42.379 + 0.04901523*Tf + 10.14333127*RH- 0.22475541*Tf*RH
$- (6.83783*10^{-3})*(Tf^{2}) - (5.481717*10^{-2})*(RH) + (1.22874*10^{-3})*(Tf^{2})*(RH)$
$+ (8.5282*10^{-4})*Tf*(RH^{2}) - (1.99*10^{-6})*(Tf^{2})*(RH^{2})$.