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Tariff

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Customer Response to RTP in Competitive Markets:
A Study of Niagara Mohawk's Standard Offer Tariff*

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Abstract

Utilizing load, price, and survey data for 119 large customers that paid competitively determined hourly electricity prices announced the previous day between 2000 and 2004, this study provides insight into the factors that determine the intensity of price response. Peak and off-peak electricity can be: perfect complements, substitutes, or substitutes where high peak prices cause temporary disconnection from the grid, as for some firms with on-site generation. The average elasticity of substitution is 0.11. Thirty percent of the customers use peak and off-peak electricity in fixed proportions. The 18% with elasticities greater than 0.10 provide 75% of the aggregate price response. In contrast to Industrial customers, Commercial/Retail and Government/Education customers are more price responsive on hot days and when the ratio of peak to off-peak prices is high. Price responsiveness is not substantially reduced when customers operate near peak usage. Diversity of customer circumstances and price response suggest dynamic pricing is suited for some, but not all customers.

1. INTRODUCTION

The enthusiasm for dynamic pricing of electricity in the 1970s, in part motivated by PURPA, was supplanted in the following two decades by the focus on other issues, such as energy efficiency and market restructuring. Recently, there has been a resurgence of interest in implementing real-time pricing (RTP) of electricity. Ruff (2002) and Borenstein, et al. (2002), among others, argue that rather than relying on rates that internalize risks, customers should decide whether or not to hedge against price volatility. In doing so, customers are motivated to evaluate the benefits of strategies for adjusting load to price changes, that would reduce price volatility in wholesale electricity markets and act as a deterrent to market power (Neenan, et al., 2002). If customers have diverse hedging needs, making RTP the retail standard offer would create opportunities for new, competitive market entrants (Flaim, 2000) to provide diversified hedging options.

These arguments have led policy-makers in some states to conclude that mandating RTP for large end users in retail markets with customer choice would achieve these goals. Products offered by competitive retail suppliers would provide customers with choices on how much price risk to bear. To increase market efficiency, others could extend that prescription to vertically integrated markets through self-selecting RTP type services (Barbose, et al., 2004).

In 1998, Niagara Mohawk Power Corporation (NMPC), now a National Grid Company, implemented a market-based, RTP-type rate as the default service for commercial and industrial customers with peak demands greater than two MW. NMPC indexes RTP energy usage rates to the NYISO's zonal day-ahead market prices. Recently, New Jersey, Maryland, and Pennsylvania have implemented a similar plan as the default service for large customers, and other states, such as Illinois, New York, and Ohio, are considering or have implemented new RTP initiatives (Barbose, et al., 2005). RTP has also attracted the attention of regulators in markets that remain vertically integrated. California, in particular, seems committed to widespread implementation of some form of dynamic pricing (CPUC, 2002) to promote price response.

The strong theoretical and philosophical foundations for implementing dynamic pricing for retail electric services are supported by market simulations, such as those by Borenstein (2005), that demonstrate long-run efficiency gains from implementing RTP. There is, however, a paucity of information in the public domain to quantify the ability of customers to respond to the imposition of RTP, a critical element of such modeling endeavors. A few empirical studies have provided measures of price responsiveness for individual firms and at an aggregate level, but typically there has been too little information to identify which customer-specific factors most influence price responsiveness (Zarnikau, 1990; Herriges, et al., 1993; Patrick and Wolak, 2001; Schwarz, et al., 2002; Boisvert, et al., 2004; Charles River Associates, 2005; Taylor, et al., 2005). Some of these studies relied on functional forms that are unable to quantify how price responsiveness is affected by weather, by the nominal level of electricity prices, and by the intensity of electricity usage. Consequently, the benefits of RTP to customers and other stakeholders remain speculative, a fact that impedes serious policy debate about the value of RTP in both competitive and regulated retail markets.

To address these shortcomings, we combine data on hourly electricity consumption and price with responses from a survey of customers paying dynamic electricity prices, to quantify more precisely differences in the price responsiveness among customers facing hourly prices. Despite the fact that RTP prices differ by hour, this analysis focuses on the price responsiveness of customers between peak and off-peak periods of the day. This view of daily electricity demand is supported by compelling evidence from survey responses (e.g. Neenan, et al., 2002 and 2003; and Goldman, et al., 2004 and 2005), and by Taylor, et al. (2005) and Patrick, et al. (2001) who find that electricity use by RTP customers during consecutive afternoon hours is complementary, but exhibits a substitute relationship with electricity use during other hours of the day. We also test for three types of response behavior, where peak and off-peak electricity are: substitute inputs; perfect complements; or substitutes for which there are times when the peak to off-peak price ratio is so large that peak electricity usage from the grid effectively goes to zero. We incorporate the effect of weather on both the intensity of use between peak and off-peak periods and on the customer's price responsiveness. We test explicitly the null hypotheses that the price responsiveness of customers is affected neither by the levels of peak and off-peak prices nor by how close customers are to their maximum demand. We proceed with an overview of NMPC's RTP default service, followed by a description of the demand model, a discussion of a strategy for estimation, and the specification of the empirical models. Finally, we discuss the empirical results and conclude by highlighting important policy implications.

2. NMPC'S PIONEERING RTP SERVICE

In 1998, NMPC redesigned its electric service offering so that large retail customers could purchase the electricity commodity from NMPC or from a competitive retailer. This introduced customer choice as part of an electricty market restructuring initiative. Other service charges, for capacity, transmission and distribution, were separated from commodity rates so that customers pay common delivery service charges to collect these revenues, regardless of their choice of electric commodity supplier. This default-service commodity tariff ("SC-3A Option One") consists of the electricity commodity prices indexed to the New York Independent System Operator (NYISO) location-based day-ahead market prices. Markups to that price collect ancillary services costs and delivery losses. An hourly price schedule with the next day's commodity prices is posted daily, by customer location and voltage level, on NMPC's website by 4:00 p.m.

At the inception of customer choice in 1998, NMPC also offered a fixed rate alternative - a forward contract referred to as "SC-3A Option Two"- to address customers' concerns about the availability of hedging opportunities in the newly established retail market. Option Two was comprised of a time-of-use rate schedule with fixed commodity prices that was applicable for up to five years. To participate, customers were required to designate the amount of peak and off-peak load to be priced under the TOU schedule in each month of the subsequent five-year period. Any additional usage was subject to the hourly RTP prices. Customers were required to pay for all nominated load regardless of whether they used it or not. About 18% of SC-3A customers elected this option for some or all of the five years.

Alternatively, customers could purchase their commodity from competitive retailers. In 2004, 63% of all eligible customers were purchasing their electricity from competitive suppliers—a 110% increase compared with 2000. Based on survey responses, competitive retailers were primarily offering physical commodity service contracts that insulated customers from hourly spot market price volatility. However, some retailers did offer service indexed to the SC-3A rate or to the NYISO day-ahead market directly.

There were other circumstances that could affect customers' price responsiveness. They could install "enabling technologies" either independently or with technical and financial assistance from the New York State Research and Development Agency (NYSERDA) specifically to affect their ability to adjust usage to price variability. Among the 76 survey respondents, almost half owned energy management control systems (EMCS) or peak load management (PLM) devices, 41% had available energy information systems (EIS), and 55 % reported on-site generation equipment.

Beginning in 2001, SC-3A customers could also participate directly in the wholesale electricity market through demand response (DR) programs implemented by the NYISO. Forty-two percent of SC-3A customers participated in the Emergency Demand Response Program (EDRP), which pays the maximum of $500/MWh or the real-time market price for load curtailments when NYISO declares emergency events, and/or the Installed Capacity/Special Case Resource (ICAP/SCR) program, which provides up-front capacity payments and entails penalties for participating customers who fail to reduce load when called upon to do so.

3. THE DATA

NMPC provided hourly electricity usage data, tariff history, basic customer characteristics and hourly prices for 146 large customer accounts eligible for default RTP service during the study period. NMPC assisted in the administration of customer surveys, which achieved a response rate of almost 50%, to collect more detailed information on retail market choices, technology endowment, load response strategies, and other adaptations to default-service RTP.

3.1. SAMPLE CHARACTERISTICS

Based on data from these sources, we determined that 119 of the 146 SC-3A customers were exposed to hourly-varying prices for some or all summer months during the 2000-2004 period (Table 1). For customers choosing Option Two or obtaining commodity service from a competitive supplier, we included daily price and load data *only* for those specific days or months during which some portion of these customers' loads were exposed to hourly prices.[1]

Among the 119 customers that faced hourly prices, 55 customers completed the survey; respondents represented the population of large customers in the SC-3A rate class quite well in terms of customer business sector and size, as measured by non-coincident peak load (Table 1).[2]

Table 1. Niagara Mohawk's SC-3A Customer Accounts, 2000-2004

			Manuf.	Gov't / Ed	Comm / Retail	Health Care	Public Works	**Total**
		SIC Codes	01 - 39	81 - 98	50 - 79	80	40 - 49	
Study Population	Accts.	Count	46	44	17	17	22	**146**
		% Total	32%	30%	12%	12%	15%	
	MW	Count	233	206	55	78	70	**642**
		% Total	36%	32%	9%	12%	11%	
Study Sample[a]	Accts.	Count	44	34	17	8	16	**119**
		% Total	37%	29%	14%	7%	13%	
	MW	Count	221	166	49	38	40	**514**
		% Total	43%	32%	10%	7%	8%	
Survey Respondents[b]	Accts.	Count	23	16	8	2	6	**55**
		% Total	42%	29%	15%	4%	11%	
	MW	Count	127	82	24	5	15	**253**
		% Total	50%	32%	9%	2%	6%	

[a] Customers were included in this category for each summer that they did not purchase a fully hedged alternative commodity service. Statistics here refer to all customers that met this criterion for at least one summer of the study, but were only included in the empirical analysis for summers in which they paid hourly prices.

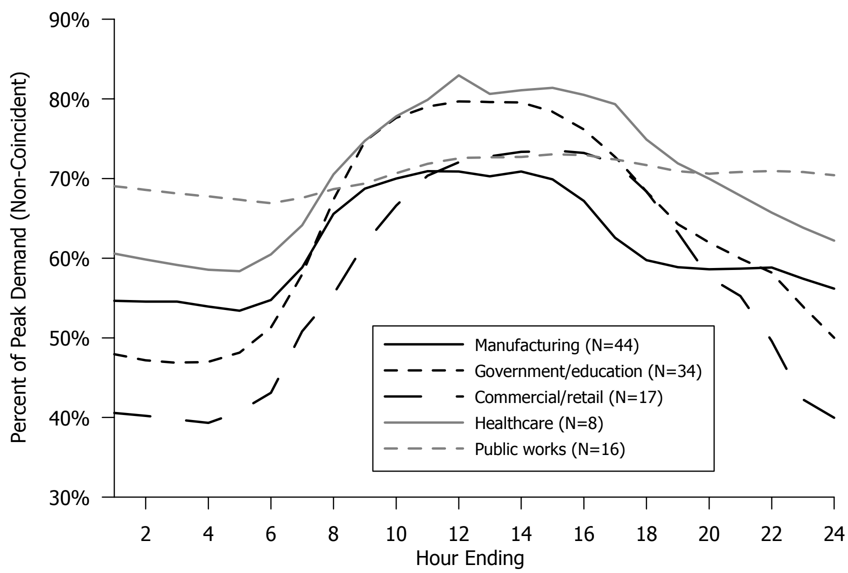
[b] Only the survey respondents that also paid hourly prices for at least one summer are shown here. Altogether, 76 customers responded to the survey.

When grouped by business class, the 119 customers exhibit stark differences in hourly load characteristics (Figure 1). The load curve for Public Works customers, for example, is nearly flat. Government/Education and Commercial/Retail establishments have large plug and HVAC loads coincident with a daily business cycle, and whose peak demands coincide with expected

[1] Of these 119 customers, about 35% faced day-ahead hourly prices for all five summers for which we have data (see Goldman, et al., 2005).
[2] A total of 76 customers responded to the customer survey; 19 of them were on fixed price contracts or tariffs during the entire study period.

high priced periods. Manufacturing customers illustrate a marked change in consumption during these high priced early to mid-afternoon hours, relative to the surrounding periods.

Figure 1. SC-3A Customer Load Profiles by Business Sector



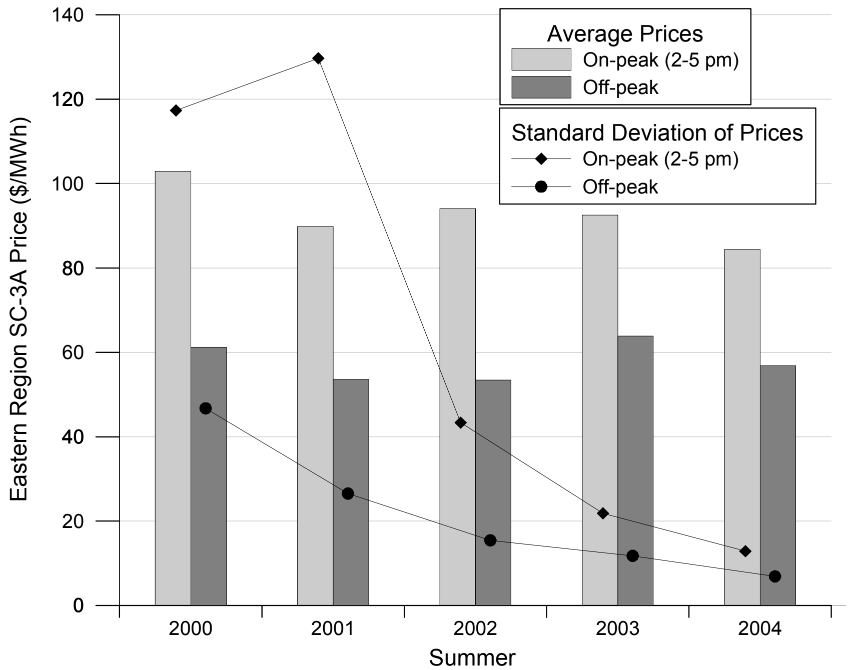
3.2. TRENDS IN SC-3A COMMODITY PRICES AT NIAGARA MOHAWK

Compared to other wholesale markets operating during the same time period (e.g., in California and other parts of the Eastern United States), day-ahead hourly prices in upstate New York, where NMPC service territory is located, were relatively stable during the study period.[3] The data in Figure 2 pertain to prices for the Capital region, one of the several NYISO pricing zones in the NMPC service territory, where prices and price volatility were highest. In other zones, SC-3A prices were slightly lower and less volatile.[4] In all pricing zones, average prices remained relatively stable throughout the study period, but

[3] NYISO day-ahead prices have been higher and more volatile in the downstate regions (e.g., New York City) where transmission capacity constraints are more frequently binding. NMPC service territory does not cover these areas.
[4] See Goldman, et al. (2005) for a more detailed analysis of prices and price volatility in various NMPC regions.

price volatility (as measured by the standard deviation of hourly prices) has declined considerably since 2001.

Figure 2. Trends in SC-3A Prices



4. THE ELECTRICITY DEMAND MODEL

For the empirical analysis, we adopt a model for electricity demand consistent with that used initially by Caves, et al. (1984), and later by King and Shatrawka (1994) and Schwarz, et al. (2002) to evaluate electricity price response.[5] Customers are assumed to optimize economic returns under a sequential, three-level profit or cost function, which is assumed to be separable in electricity usage.[6] At the first level, weekday electricity usage is allocated between defined peak and off-peak periods reflecting differences in the price and value of electricity. At the second level, customers are assumed to allocate

[5] The model is also conceptually similar to the consumer demand model discussed by Braithwait (2000).

[6] For manufacturing and other business firms, the assumption of profit maximization is appropriate, and it also implies that firms minimize the cost of electricity usage in each of the three separable stages. Caves, et al. (1981) and Cowing and Holtmann (1983) argue convincingly that service industries, governmental institutions and common carriers attempt to minimize the cost of providing service levels that are exogenously determined. Thus, as is done below, we are able to model this separable electricity demand by first specifying an indirect electricity cost function for all firms and institutions in our sample.

monthly usage between weekdays and weekends. At the third level, customers are assumed to determine their overall electricity expenditures as a proportion of their total production costs.

We focus on the allocation of daily electricity usage between the high-price hours (peak) and low-price (off-peak) hours of each day.[7] Due to the continuous nature of electricity supply and usage, defining what constitutes peak and off-peak is an empirical question driven by prices and the circumstances by which customers use and value electricity. Studies of price response to time-of-use (TOU) rates typically utilize either pooled data for customers participating in different TOU rates or data that are pooled across several treatments where prices or the definition of the on-peak period vary by the experimental design (Caves, et al., 1984; Patrick, 1990; Braithwait, 2000). To establish a uniform definition of distinct electricity commodities, peak and off-peak electric energy, Caves, et al. (1987) identified six separate commodities facing customers. A six-hour afternoon pricing period was divided into one two-hour commodity and one four-hour commodity. The other hours of the day were aggregated into four separate commodities. The authors argued that this sub-aggregation was needed to characterize behavior in response to prices that are high for only very short periods. In other words, they assumed that electricity within each aggregation was complementary.

Extending this structure to hourly RTP-type programs would lead to 24 electricity commodities. Such an extensive specification would be warranted only if industrial and commercial customers adjust usage on an ongoing basis to changing hourly prices. Recently, Taylor, et al. (2005) analyzed the hourly price elasticity of large commercial and industrial customers served under a day-ahead RTP rate to identify patterns based on whether electricity use in certain hours was a complement or a substitute for electricity use in other hours. They report

[7] Few analysts have attempted to estimate all three levels of electricity demand. Caves, et al. (1984) is an exception.

that generally electricity use during several consecutive afternoon hours appears to be complementary—thus constituting a single electricity commodity. In turn, this single commodity exhibits a substitution relationship with electricity use during the other hours of the day. These results confirm an earlier conclusion of Patrick and Wolak. (2001), and when combined the two studies offer strong empirical support for our use of a peak/off-peak electricity demand specification.

There is also compelling evidence from customers that they implicitly characterize the day as being comprised of an on-peak and off-peak period (Neenan, et al., 2002a, b and 2003). While the specification of what comprises the peak hours may be customer specific, common business practices, driven in large part by traditional rate structures, support a bifurcation of the day that captures most of the variation in usage. Accordingly, we assume that daily electricity decisions involve the allocation of electricity usage, and the rearrangement of business activity, between high-price hours (peak) and low-price (off-peak) hours of summer days on which SC-3A prices deviate from the average most often. Over 75% of prices above $0.20/kWh during the study period occurred between 12 Noon and 6:00 p.m., and typically appeared in clusters of four or more consecutive hours. In other months, prices exceeded that threshold infrequently, and then only in isolated hours. For this study, the definition of the peak and off-peak period is determined empirically.

4.1. ESTIMATING LARGE CUSTOMERS' DEMAND FOR ELECTRICITY

To formulate a demand model for electricity, we define a customer's production function as:

$$Q = F\left(x_1, x_2, ..., x_n, E\left(k_p, k_o\right)\right) \tag{1}$$

where Q = customer output; x_i = non-electricity production inputs; k_p = peak-period electricity usage; and k_o = off-peak electricity usage. By assuming that production is separable between daily electricity inputs and other inputs, daily peak and off-peak electricity inputs are, in turn assumed, to be combined according to the aggregator function, E, within the function F. Any combination of k_p and k_o that yields the same value for E is equally productive in producing the firm output, Q, other factors of production constant.

From duality theory (Shephard, 1970), we specify an indirect cost-minimizing electricity cost function, C.[8] Assuming a generalized Leontief (GL) functional form:[9]

$$C = E\left(d_{pp} p_p^{1/2} p_p^{1/2} + d_{po} p_p^{1/2} p_o^{1/2} + d_{op} p_o^{1/2} p_p^{1/2} + d_{oo} p_o^{1/2} p_o^{1/2}\right) \tag{2}$$

where E is effective electricity; p_p and p_o are prices for peak and off-peak electricity, respectively, and d_{pp}, d_{po}, d_{op}, and d_{oo} are parameters to be estimated.[10]

[8] 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 into the direct cost function, thus allowing one to write the cost-minimizing cost function in terms of output and input prices.

[9] In conducting this analysis, there were a number of other second-order flexible forms that might have been used in the empirical specification. One such commonly used flexible form, the translog (TL) model (Boisvert, 1982 and Chambers, 1988) would have avoided estimating any equations that are non-linear in the parameters. The TL model relies on estimating a set of electricity cost share equations that are linear in the model parameters and does not require observations on the electricity aggregate. While this TL form was particularly attractive from an estimation perspective, this alternative was not pursued because as Caves and Christensen (1980a, b) point out, the TL model does not perform well when substitution elasticities are likely to be small, or when there are likely to be small shares or large relative differences among shares. This is partly true because the translog has the Cobb-Douglas form (a form that implies unitary elasticities of input substitution) as a special case. Patrick and Wolak (2001) found this to be problematic in an application of customer demand for electricity under real time pricing and argue that the GL model is superior to the TL model because it has a fixed-coefficient Leontief technology as a limiting case, and therefore, it can reflect rather modest substitution possibilities. However, these authors also note that if one imposes global concavity, the GL model loses some of its flexibility—in particular all inputs must be substitutes. To circumvent these difficulties related to both the TL and GL models, Patrick and Wolak (2001) and Taylor, et al. (2005) employ a Generalized McFadden (GM) cost function that is "…second-order flexible, yet suited to capture small positive and negative elasticities of substitution between electricity demands across load periods within a day" (Patrick and Wolak, 2001, p. 27). Their need to accommodate both positive and negative elasticities of substitution results from their specification of more than two demand periods. However, our empirical model specifies only two demand periods. In this case, any model in which global concavity is either assumed, or imposed, requires that the inputs be substitutes. Therefore, the primary issue that led to their selection of the GM model is of no concern in our present application of the GL indirect cost model.

[10] As with all indirect cost functions, the GL function is linear homogeneous in all prices. Furthermore, Diewert (1971) shows that when the GL indirect cost function (or any other indirect cost function) is decomposed in this fashion, the underlying aggregator function for E exhibits constant returns to scale.

Also from Shephard (1970), the optimal (constant output) demands for peak and off peak electricity can be determined by differentiating (2) with respect to each price:

$$\partial C / \partial p_p = k_p = E\left[d_{pp} + d_{po} \left(p_p / p_o \right)^{1/2} \right] \quad (3)$$

$$\partial C / \partial p_o = k_o = E\left[d_{oo} + d_{op} \left(p_o / p_p \right)^{1/2} \right] \quad (4)$$

According to Berndt (1991), the Allen partial elasticities of input substitution for the GL model are:

$$\sigma_{op} = \frac{\left[C d_{op} \left(p_p p_o \right)^{-1/2} \right]}{2\left[E a_p a_o \right]} \quad (5)$$

where $a_p = k_p / E$ and $a_o = k_o / E$.

4.2. RELATING THE PARAMETERS TO THE PARTIAL ELASTICITIES OF SUBSTITUTION

It is well known that the cross Allen partial elasticity of substitution in the two-input case (equation (5)), is equal to the direct elasticity of substitution, defined as the percentage change in factor intensities as the inverse price ratio changes by one percent, holding a customer's energy aggregate (and therefore output) constant. In the GL model, the elasticities of substitution differ, depending on the price ratio and there is no guarantee that the function is well behaved at each data point; specifically that $\infty > \sigma_{op} \geq 0$ (Ferguson 1969).[11]

However, a sufficient condition for the GL function to be well behaved is for all parameters to be non-negative (Diewert, 1971); a necessary condition is that $d_{op} \geq 0$. For this reason, three situations particularly significant for daily electricity demand can be readily identified.

[11] At each data point, the estimated cost function must be monotonically increasing and strictly quasi-concave in input prices. Consequently, we must verify that the fitted values for all the input-output equations are positive and that the "n x n" matrix of the σ_{ij} substitution elasticities is negative semi-definite at each observation (Berndt, 1991, p. 465).

Case 1: If d_{pp}, d_{op}, and d_{oo} are all non-negative, then peak and off-peak electricity are substitutes, $\sigma_{op} > 0$. This is the most typical relationship between two inputs.

Case 2: If d_{op} takes on an extreme value of zero, then for the function to be well behaved, $d_{pp} \geq 0$ and $d_{oo} \geq 0$, with at least one strict inequality. The GL model reduces to the ordinary two-factor Leontief production function; peak and off-peak electricity are perfect complements, $\sigma_{op} = 0$, and there is no opportunity for input substitution. Because this situation is captured by one coefficient in the model, we have a means to identify customers with fixed proportions in their customer's peak and off-peak electricity usage.

Case 3: For this case, we have $d_{pp} < 0$, $d_{op} > 0$, and $d_{oo} > 0$. Here, $\sigma_{op} > 0$, but there is a price of peak and off-peak electricity, p_p^* and p_o^*,at which the peak to off-peak price ratio is so large that peak electricity is no longer used. This happens when $p_o/p_p < d_{pp}^2/d_{oo}^2$. This case may depict very well the behavior of customers with on-site generation, as suggested by Taylor, et al. (2005). Although the customer may still use peak electricity, demand for peak power from the grid falls to zero as the price ratio of electricity rises to this critical level. The customer would rely upon on-site generation for its peak electricity.

4.3. ESTIMATING THE PARAMETERS OF THE GL MODEL

Ordinarily by assuming an additive error structure associated with the input share equations a_p and a_o,the parameters of the GL cost function can be estimated as a system of equations, However, in our case, the energy aggregate E (from equation (1)) is an unspecified function of peak and off-peak energy usage, and E cannot be observed in the data. Therefore, to estimate the parameters of the model, we specify a single equation which is the logarithm of the ratio of a_p and a_o:[12]

$$\ln\left(\frac{a_p}{a_o}\right) = \ln\left(\frac{k_p}{k_o}\right) = \ln\left\{\frac{\left[d_{pp} + d_{po}\left(p_o / p_p\right)^{1/2}\right]}{\left[d_{oo} + d_{op}\left(p_p / p_o\right)^{1/2}\right]}\right\} \quad . \tag{6}$$

Denoting estimated parameters from equation (6) as d_{ij}*, we can calculate $(a_p)_{\text{fit}}$ and $(a_o)_{\text{fit}}$ at each data point. We can also substitute the estimated parameters from equation (6) into equation (2) to obtain estimates of $(C/E)_{\text{fit}}$. Finally, these three expressions can be substituted into equation (5) to obtain for each data point estimates of:

$$\sigma_{op} = \frac{\left[\left(\frac{C}{E}\right)_{fit} d_{op}{}^{*}\left(p_p p_o\right)^{-1/2}\right]}{2\left(a_p\right)_{fit}\left(a_o\right)_{fit}} \tag{7}$$

4.4. EMPIRICAL ANALYSIS

The GL model's flexible form is well suited for characterizing potentially diverse customer price response behavior. To calculate elasticities of substitution according to the procedures outlined above, we first estimate for each customer, f:

$$\begin{aligned}\ln\left[k_{p,t,f} / k_{o,t,f}\right] = w_f W_{t,f} &+ \left\{\ln\left[h_{p,f} H_{t,f} + d_{pp,f} + d_{po,f}\left(p_{o,t,f} / p_{p,t,f}\right)^{1/2}\right]\right\} \\ &- \left\{\ln\left[h_{o,f} H_{t,f} + d_{oo,f} + d_{op,f}\left(p_{p,t,f} / p_{o,t,f}\right)^{1/2}\right]\right\} + \varepsilon_{t,f}\end{aligned} \tag{8}$$

where t is the index for weekday observations, $k_{p,t,f}$ = peak usage (kWh); $p_{p,t,f}$ = average daily peak price (\$/kWh); $k_{o,t,f}$ = off-peak usage (kWh); $p_{o,t,f}$ = average daily off-peak price (\$/kWh); $\varepsilon_{t,f}$ = a random error term; and w_f, $h_{p,f}$, $h_{o,f}$,

[12] This specification is equivalent to modeling the ratio of equations (3) and (4), and it is necessary in order to eliminate the unobservable energy aggregate from the estimating equations. For this reason, we are limited to a homothetic form of the indirect cost function (equation (2)). Thus, unlike Taylor and Schwarz (1990), we are unable to test both homothetic and non-homothetic versions of a Generalized Leontief specification.

$d_{pp,f}$, $d_{po,f}$, $d_{op,f}$, and $d_{oo,f}$ are parameters to be estimated. The effect of weather is accounted for in two distinct ways.[13] The variable $W_{t,f}$ measures cooling degrees (e.g., the difference between the average peak period temperature and 65 degrees F). It enters as an intercept shifter, thus controlling for inherent differences in peak to off-peak usage as temperature changes. The variable $H_{t,f}$ is a binary (0,1) variable to distinguish hot ($H_{t,f} = 1$ when Avg. THI ≥ 85 during peak periods) from cool days ($H_{t,f} = 0$ when Avg. THI < 85 during peak periods), defined by the temperature heat index (THI).[14] This variable allows the model parameters to differ on hot and cool days.[15]

From the estimated model described in equation (8) we generate a substantial number of estimates of daily elasticities of substitution for each customer. Therefore, to ascertain if the level of price response is affected by the nominal level of electricity prices and/or differs systematically by type of business and by the intensity of electricity use, we estimate an additional model by pooling the elasticity estimates across customers.[16] The variables defined to measure these factors are specified in the model as intercept and/or slope shifters to account for interaction among the characteristics. The pooled model is:

$$\begin{aligned}\sigma_{tf} &= \alpha + \beta_1\left(p_{p,t,f} / p_{o,t,f}\right) + \beta_2 Man\left(\%MaxD_{t,f}\right) + \beta_3 Man\left(p_{p,t,f} / p_{o,t,f}\right) \\ &\quad + \beta_4 GovEd\left(\%MaxD_{t,f}\right) + \beta_5 GovEd\left(p_{p,t,f} / p_{o,t,f}\right) \\ &\quad + \beta_6 PW\left(\%MaxD_{t,f}\right) + \beta_7 PW\left(p_{p,t,f} / p_{o,t,f}\right)\end{aligned}$$

[13] The complexity of this non-linear equation precludes the inclusion of a number of additional variables to account for effects of important customer characteristics, etc. on the parameter estimates and the subsequent elasticities of substitution. It was possible to include two additional variables. We chose to identify the effects of weather primarily because electricity demand is thought to be weather-sensitive, and while weather would vary over time for each customer, there would likely be less variability across customers due to their geographic proximity in upstate New York.

[14] The Temperature Heat Index is constructed from temperature and dew point values for five National Weather Service stations located in the utility's service territory. See Goldman, et al. (2005) for details.

[15] We used FIML methods within PROC MODEL in SAS, $d_{po,f} = d_{op,f}$ to ensure symmetry. We also require that $d_{oo,f} + d_{pp,f} + d_{op,f} + d_{po,f} = 1$ and $h_{p,f} = h_{o,f}$, normalizing to reflect a unit isoquant for the energy aggregate. The parameter estimates changed if this condition were set to a different number, but the estimates of the elasticities of substitution were invariant. The Durbin-Watson test indicated the data was serially correlated, so an AR(1) correction was added to the model.

[16] This strategy for analyzing these types of results is similar to the one used by Taylor and Schwarz (1990). They estimated household demand response, and pooled the corresponding GL parameter estimates for each cross section in their data. Then, using each set of estimated parameters as the dependent variable in a regression model, they determined the extent to which the parameter estimates were affected by weather and customers' prior experience with TOU rates.

$$+\beta_8 ComRtl\left(\%MaxD_{t,f}\right)+\beta_9 ComRtl\left(p_{p,t,f}\,/\,p_{o,t,f}\right)+u_{tf} \qquad (9)$$

where $p_{p,t,f} / p_{o,t,f}$ = ratio of peak to off-peak electricity prices on day t for customer f; $\%MaxD_{t,f}$ = peak use on day t as a percentage of customer f's maximum summer demand; *Man* = 1 for Manufacturing customers, 0 otherwise; *GovEd* = 1 for Government/Education customers, 0 otherwise; *PW* = 1 for Public Works customers, 0 otherwise; *ComRtl* = 1 for Commercial and Retail customers, 0 otherwise; u_{tf} = a random error term; and α and β_i (i =1,…,9) are parameters to be estimated.

5. FINDINGS AND IMPLICATIONS

Estimating the GL model (equation (8)) requires specifying what hours of the day constitute the peak period. To accomplish this, we examined the estimated elasticities of substitution, calculated according to the procedures in equations (6) and (7), to see how they are affected by the length and timing of the peak period. The results for three alternative peak period definitions—12 Noon.–5:00 p.m., 1:00–5:00 p.m., and 2:00–5:00 p.m.—are shown in Table 2. The three-hour peak period (2:00–5:00 p.m.) produces the highest elasticities of substitution, suggesting that this period best reflects a peak period in which the electricity use in the hours included in the peak are complementary inputs, as described by Taylor, et al. (2005). Furthermore, since the prices for SC-3A customers typically reach their highest levels between the hours of 2:00 and 5:00 p.m., this period has particular policy significance. For this reason, and for the fact that the statistical performance (which is discussed in some detail below) is similar for all three peak periods, the remainder of the discussion focuses on the weekday afternoon hours of two to five.

Table 2. Load-Weighted Elasticities of Substitution by Sector and Peak Period

Peak Period	N	Manuf.	Gov't / Ed	Comm / Retail	Health Care	Public Works	**Total**
	N	44	34	17	8	16	119
12 noon to 5 p.m.	Min.	0.00	0.00	0.01	0.00	0.00	0.00
	Avg.	0.07	0.04	0.03	0.04	0.01	0.05
	Max.	0.09	0.05	0.04	0.05	0.01	0.06
1 p.m. to 5 p.m.	Min.	0.12	0.07	0.05	0.03	0.01	0.08
	Avg.	0.12	0.08	0.06	0.04	0.01	0.09
	Max.	0.14	1.21	1.43	0.04	0.01	0.63
2 p.m. to 5 p.m.	Min.	0.15	0.09	0.05	0.03	0.01	0.10
	Avg.	0.16	0.10	0.06	0.04	0.02	0.11
	Max.	0.18	0.42	1.49	0.04	0.02	0.38

5.1. AVERAGE ELASTICITIES OF SUBSTITUTION

For the peak period 2:00 p.m. to 5:00 p.m, the load-weighted average elasticity of substitution for the 119 customers in the sample is 0.11 (Table 2). The highest average elasticity (0.16) is in the Manufacturing sector. Government/Education customers are also quite price responsive (0.10), a group of customers whose potential to respond to price is thought by many to be small. Commercial/Retail, Health Care, and Public Works customers, with respective sector-average elasticities of substitution of 0.06, 0.04, and 0.02, are much less price responsive.

5.2. EFFECTS OF WEATHER

To identify the effects of weather both on customer electricity demand and on price responsiveness, we incorporated two weather variables, an intercept and a slope shifter, into the GL model (equation (8)). The number of customers for which these variables are statistically significant, and the corresponding signs of the parameter estimates are shown in Table 3.

The weather intercept variable reflects the relationship between daily cooling degrees and customer's electricity demand and was statistically significant for 58 of the 119 customers (49%); most of the significant parameters were positive, indicating that on hot days, peak usage for these customers increases disproportionately relative to off-peak usage, all else equal. As expected, the Government/Education, Commercial/Retail and Health Care, which are characterized by large cooling loads, exhibit the most weather-sensitive peak loads; for at least 65% of customers in each of these sectors the estimated coefficients are positive.

The slope shifters measure the effect of weather on the intensity of price responsiveness. For example, customers with weather-sensitive loads may be more price responsive on hot days if these loads are discretionary.[17] However, the coefficients on this variable are significant for only 32 customers (27%) and are usually negative. These customers are less able or willing to shift load from peak to off-peak when peak prices rise. Significant results were observed for more than 40% of customers in only two sectors (Commercial/Retail and Health Care).

[17] Although 22% of the survey respondents reported that they shift load from peak to off-peak periods in response to high prices, another 49% reported that they curtail discretionary loads, such as lighting or air conditioning, without making up the foregone usage at another time. Since the reduction in discretionary load during peak periods reduces relative peak to off-peak usage, such behavior is still properly accounted for in the elasticity of substitution, even though there is no associated increase in off-peak load.

Table 3. Effects of Weather on Demand and Price Responsiveness

			Manuf.	Gov't / Ed	Comm / Retail	Health Care	Public Works	**Total**
		N	44	34	17	8	16	**119**
Significant Results[a]	Weather Intercept	Positive	7	22	12	6	5	**52**
		Negative	3	1	1	0	1	**6**
	Weather Slope	Positive	2	0	3	1	0	**6**
		Negative	7	8	4	3	4	**26**
Average Substitution Elasticity		Cool Days (THI[b]<85)	0.16	0.10	0.05	0.04	0.02	**0.11**
		Hot Days (THI[b]≥85)	0.15	0.12	0.10	0.04	0.02	**0.11**

[a] 10% significance level.

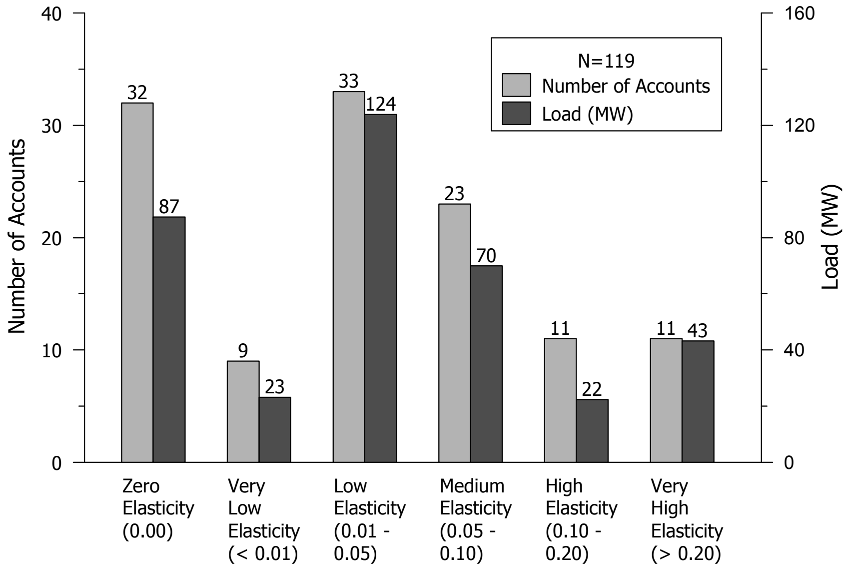
[b] THI = Temperature Heat Index - average for the hours from 2-5 p.m.

Table 3 also illustrates the combined, overall effect of weather on price responsiveness, reporting load-weighted elasticities of substitution on cool days and on hot days. For all customers taken as a group, there is essentially no difference in the average elasticities of substitution on hot and cool days. The sector-level results, however, reveal that customers for whom cooling needs drive a substantial proportion of energy usage—Government/Education and Commercial/Retail sectors—exhibit marked increases in overall price responsiveness on hot days, 20% and 100%, respectively. Manufacturing customers, on the other hand, appear to be only slightly less price-responsive on hot days. For other sectors, the effect is minimal.

5.3. DIFFERENCES IN PRICE RESPONSIVENESS AMONG CUSTOMERS

Estimating customer-level demand models allowed us to explore the heterogeneity of price responsiveness among the study customers. Figure 3 contains the distribution of elasticities of substitution by customer account and non-coincident peak demand. For the most part, customers' maximum electricity demands are distributed in similar proportions to their numbers. Thus, contrary to some common expectations, it appears that price responsiveness is not primarily driven by customer size, at least among customers with peak demands greater than two MW.

Figure 3. Distribution of Elasticities of Substitution by Account and Maximum Demand



By examining this figure, we are able to gain an understanding of the number of customers in our sample whose ability to respond to price is characterized by one of the three cases mentioned above, that is where peak and off-peak electricity: (1) are substitute inputs; (2) are used in fixed proportions; and (3) are substitutes up to a threshold price at which point peak power from the grid is "priced" out of the market, customers may substitute on-site generation.

About one-quarter of customers (28% of the accounts and 24% of the load) appears to use peak and off-peak electricity in fixed proportions (the "zero elasticity" group in Figure 3);[18] the remaining firms have positive elasticities of

[18] Since a sufficient condition for peak and off-peak electricity to be required in fixed proportions is that the estimated coefficient d_{op} from equation (8) be zero, it is encouraging that for all 32 customers in this group, d_{op} is either zero or based on a simple t-test not significantly different from zero. Since the elasticities of substitution are non-linear functions of the GL parameter estimates (following equation (7)), we also calculated standard errors for the elasticities of substitution by the delta method described by Greene (2003). Based on these calculations at the mean level of prices, the elasticity of substitution is less than twice its standard error for all but two of the customers in this group. This is additional evidence that these customers use peak and off-peak electricity in fixed proportions.

substitution, indicating that peak and off-peak electricity are substitute inputs. A large group of customers (35% of the accounts and 40% of the load) are only slightly responsive (elasticities of substitution of less than 0.05).[19] About 20% are moderately responsive, with elasticities of substitution between 0.05 and 0.10. Finally, the 18% of customers in the high and very high groups (elasticities of substitution greater than 0.10) provide 75-80% of the 119 customers' aggregate demand response.[20]

Among this final group, we also identified five customers—four Government/Education customers and one Commercial/Retail customer—whose parameter estimates suggest that they would curtail grid-supplied peak electricity usage at a threshold peak to off-peak price ratio. The threshold price ratio ranged from 7:1 to over 100:1. In responses to the survey, all of these customers indicated that they had on-site generating capacity.[21]

Because of the availability of information from NMPC and the customer survey responses, we are also able to document the price responsiveness of those customers who participated in the Emergency Demand Response Program, one of the NYISO's demand response programs. As shown in Figure 4, EDRP participants are distributed throughout the several categories of price responsiveness. However, only two groups with the highest elasticities of substitution have more EDRP participants than non-participants. There are a

[19] We calculate standard errors for the elasticities of substitution by the delta method for these two groups of customers as well. For all customers in the group whose elasticities of substitution are less than 0.01, the standard elasticity of substitution is less than twice its standard error, evidence that the elasticities are not statistically different from zero and that these customers also use peak and off-peak electricity in fixed proportions, or nearly so. For 27 of the 33 customers in the group whose elasticities of substitution are between 0.01 and 0.05, the average elasticity of substitution is also less than twice its standard error. Again this is as it should be, particularly for firms at the low end of the range.

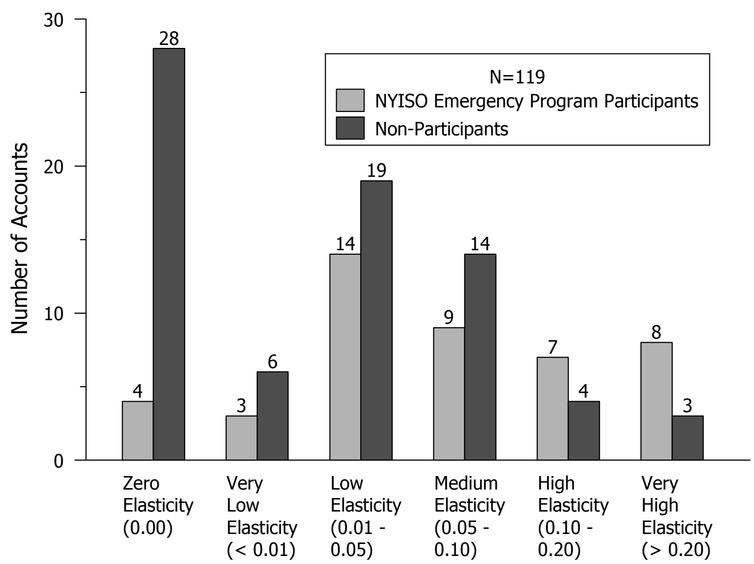
[20] For each of the 11 customers in the group whose elasticities of substitution are above 0.20, the average elasticity of substitution is greater than twice its standard error, providing strong statistical evidence for the magnitude of their price responsiveness. For the remaining two groups (those with elasticities of substitution between 0.05 and 0.10 and between 0.10 and 0.20, the results are mixed. For about half the customers in each group, the estimated elasticities of substitution are greater than twice their standard errors. Most of the customers in these two groups for which the elasticitities of substitution are not statistically different from zero are Manufacturing firms.

[21] A number of other survey respondents have on-site generation capacity; they appear much less price responsive because for most of them the on-site generation is used primarily to meet emergency backup requirements.

couple of possible explanations for the association of EDRP participation and price responsiveness. First, customers who are naturally more price responsive may be more likely to enroll in EDRP, as they see a greater opportunity to benefit from participation. We attempted to capture this added incentive in estimating the demand model by substituting the minimum EDRP incentive of \$500/MWh as the effective price, and not the prevailing day-ahead price, during program events. Second, while 63% of the survey respondents participating in EDRP reported reducing load to earn curtailment payments, 59% also indicated that they respond in part due to a perceived civic duty to help keep the electric system secure.

It is more difficult to explain why there are 30 EDRP customers among the groups with the lowest elasticities of substitution. It appears that these customers may have enrolled in EDRP, only to find out later that they were unable to reduce loads during EDRP events, or that the financial incentives were too small to do so. Since load reduction performance during EDRP events is voluntary, there is no penalty for non-compliance.

Figure 4. Distribution of Accounts by Elasticity of Substitution and NYISO Program Participation



The presence of an Energy Management Control Systems (EMCS) would seem to facilitate shifting load in response to higher relative peak prices. It was somewhat surprising that among the 22 customers that had purchased a system, only three of the respondents had elasticities of substitution above the overall average. However, in responding to additional survey questions, fewer than 20% of these customers said they used the EMCS to facilitate short-term price response; instead, most respondents used the EMCS to achieve energy-efficiency or peak load reduction goals.

5.4. EFFECTS OF PRICES AND DEMAND INTENSITY ON DAILY PRICE RESPONSE

As the second component of this empirical analysis, we estimated a model (equation (9)) to identify systematic relationships between day-to-day differences in electricity usage attributable to customers' price response, peak to off-peak price ratios and customers' daily usage as a proportion of their summer peak demand. We included interaction terms (the products of business-sector dummy variables with these factors) to determine if these effects differ by business sector. The parameter estimates are presented in Table 4. The statistical performance of the model is quite good—the R^2 is high and all of the coefficients are statistically significant.[22]

[22] This model was initially estimated by generalized least squares, using an AR(1) process to correct for autocorrelation in the residuals due to a strong, time-dependent persistence of similar elasticities on consecutive days. Any variations around this trend, due to the explanatory variables in the model, are reflected in the resulting parameter estimates. The high R^2 value is primarily the result of this correction. Using White's test for heteroskedasticity, we found that the residuals were systematically related to the factors that make a customer more or less price responsive on a particular day. To correct for the heteroskedasticity, we re-estimated the model using the generalized method of moments.

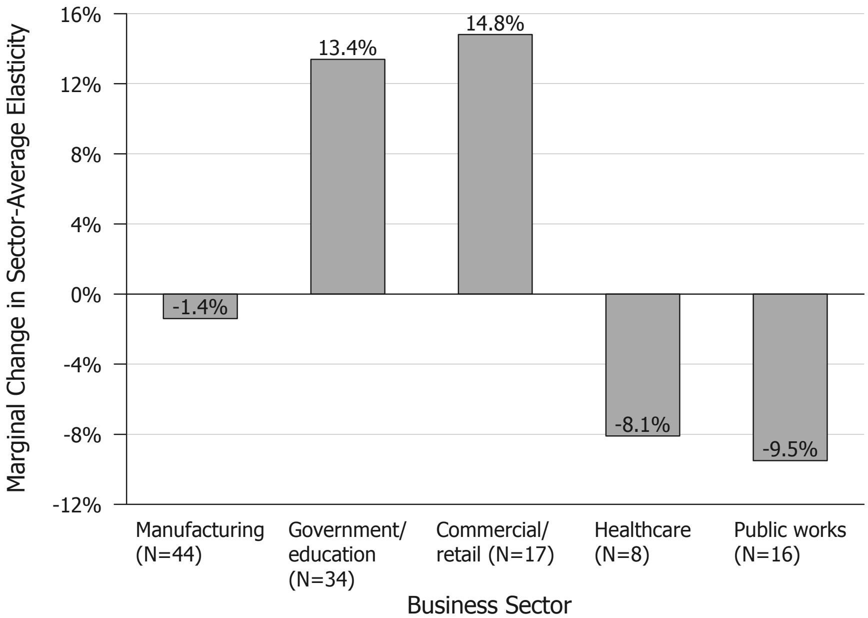
Table 4. Estimated Elasticity of Substitution Regression Model Results

Variable	Parameter Estimate	t-Statistic
Pk Off-Pk Price Ratio (PR)	-0.0028	-8.92
Commercial/Retail * PR	0.0199	4.22
Manufacturing * PR	0.0016	2.34
Gov't/Education * PR	0.0241	3.44
Public Works * PR	0.0010	2.80
% of Max Demand (MD)	-0.0513	-1.99
Commercial/Retail * MD	0.0646	2.43
Manufacturing * MD	0.0487	1.89
Health Care * MD	0.0514	2.00
Public Works * MD	0.0509	1.97
AR(1)	0.4657	8.82
N = 119 R^2 = 0.99	DW Statistic = 2.13	

Since many of the variables involve interaction terms, an effective way to interpret the results is to estimate the changes in elasticity resulting from a specified change in the explanatory variables. For each business sector, the change in the elasticity of substitution due to a unit increase in the price ratio (e.g., from 2:1 to 3:1) is shown relative to the sector's un-weighted average elasticity in Figure 5. The results indicate that Government/Education and Commercial/Retail customers curtail peak usage more on days with higher price ratios than on moderately priced days.[23] Because days in which the price ratios are high are highly correlated with days in which nominal peak prices are also high, we can infer that these customers tend to be more price responsive as prices increase.[24] The opposite is true for other sectors, although the magnitude of the effect is not as large and, in the case of Manufacturing customers, is negligible.

[23] In interpreting these results, it is important to recall that the estimated elasticities of substitution already account for the effect of weather. Thus, these results isolate the effects of the level of prices on price responsiveness, net of any weather effects.
[24] In specifying the regression models, the daily elasticities of substitution for all customers were regressed on the peak-to-off peak price ratio, which maintains consistency with the interpretation of the elasticity of substitution. Our inference that these results translate to higher nominal peak prices is supported by two factors. First, nominal peak prices are correlated with price ratios—off-peak prices seldom rise at the same rate as peak prices, so price ratios tend to rise in accordance with nominal peak prices. Second, we estimated an alternative specification in which daily elasticities were regressed against nominal peak prices and obtained similar, but slightly less statistically robust, results (see Goldman, et al., 2005, Appendix C).

Figure 5. Marginal Changes in Elasticity of Substitution from a 50% Increase in the Peak to Off-Price Ratio



A similar analysis shows that unit increases in customers' daily usage (e.g., from 60% to 70% of maximum demand) results in much smaller marginal changes in sector-average elasticities of substitution, from –3.2% for Government/Education customers to 1.2% for Commercial/Retail customers.

6. SUMMARY AND CONCLUSIONS

In this study, we characterize the price responsiveness of customers that face market-based electricity prices by combining customer hourly load and price data with survey information to characterize business circumstances. The price responsiveness of these customers, as measured by the load weighted average elasticities of substitution, is modest, 0.11—a 10% increase in the peak to off-peak price ratio leading to a 1.1% reduction in demand. At one extreme, nearly 30% of the customers appear to use peak and off-peak electricity in fixed proportions. About 9% exhibit average elasticities of substitution less than 0.01. About 75% of the aggregate price response is concentrated in the 18% of customers with the highest elasticities of substitution, those greater than 0.10. The remaining customers exhibit modest price responsiveness, with average elasticities of substitution ranging from 0.01 to 0.05. In the aggregate, we estimate that when peak to off-peak electricity prices reach a ratio of 5:1, the highest ratio during the study period, these 119 customers would reduce their peak-period usage by about 50 MW, approximately a 10% reduction from their typical usage.

Industrial customers are the most price responsive, perhaps as expected. However, Government/Education customers are quite price responsive as well, and as a group Commercial/Retail customers are somewhat less price responsive. Equally important, our study documents that for these latter two groups, the elasticities of substitution are higher, both on hot days, and on days in which peak to off-peak prices are high. These results in part reflect the discretionary nature of some load for these customers and stand in sharp contrast to those for Manufacturing firms. Furthermore, there is no evidence that the price responsiveness of any customer group is substantially reduced during days in which they are operating at or near their peak usage. Through customer survey responses, we know that customers use EMCS primarily to generally reduce peak load, thus appearing less price-responsive than might be expected. It is also true that while some customers do use on-site generation to respond to price, others use it primarily for emergency backup.

In conclusion, these results are consistent with portfolio substitution elasticity estimates for large industrial customers on voluntary RTP tariffs at vertically integrated utilities (Herriges, et al., 1993; Schwarz, et al., 2002; Boisvert, et al., 2004; and Taylor, et al., 2005), and suggest that the retail market context for RTP (i.e. two-part hedged vs. one-part market-based designs) does not greatly influence the price response behavior of industrial customers. In other words, the estimates of elasticities of substitution associated with two-part

RTP service can be extended to similarly constructed RTP pricing plans in competitive markets where all load is exposed Furthermore, these results add substantial support for the hypothesis that average price responsiveness conceals the diversity of response among customers even within the same business classifications, and that size along is not enough to predict price response. It is only through knowing something about the specific customer characteristics or circumstances that one can understand why certain customers in a particular business class are price responsive and others are not.

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