INDUSTRIAL ENERGY CONSUMER RESPONSE TO WHOLESALE PRICES IN THE RESTRUCTURED TEXAS ELECTRICITY MARKET

(DRAFT)

Jay Zarnikau[1], Greg Landreth, Ian Hallett, and Subal C. Kumbhakar

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Abstract

This paper analyzes the responsiveness of the twenty largest industrial energy consumers in the Houston area to wholesale price signals in the restructured Electric Reliability Council of Texas (ERCOT) market. Statistical analysis of the load patterns of the twenty largest Houston-area industrial electricity consumers employing a Symmetric Generalized McFadden cost function model suggests that ERCOT achieved limited success in establishing a market that facilitates the responsiveness of large industrial energy consumers to wholesale price signals in its second year of retail competition. ERCOT has sought to promote demand response without reliance on "stand alone" demand response programs for this market segment. It is suspected that this muted response is largely because energy consumers who opt to offer their "interruptibility" to the market as an ancillary service are constrained in their ability to respond to wholesale energy prices.

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[1] Author for correspondence: Jay Zarnikau is president of Frontier Associates and a visiting professor in applied statistics at the University of Texas at Austin. Contact information: Frontier Associates, 4131 Spicewood Springs Rd., Suite O-3, Austin, Texas, USA 78759; Phone: 1+ 512/372-8778; Email: jayz@frontierassoc.com. Greg Landreth and Ian Hallett are graduate students in the LBJ School of Public Affairs at the University of Texas at Austin. Subal C. Kumbhakar is a professor of economics at S.U.N.Y.-Binghamton.

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INTRODUCTION

As noted by FERC (2002): “Demand response is essential in competitive markets, to assure the efficient interaction of supply and demand, as a check on supplier and locational market power, and as an opportunity for choice by wholesale and end-use customers.” As electricity markets are redesigned to facilitate wholesale and/or retail competition, stakeholders and policymakers are faced with the challenge of ensuring that consumers are presented with accurate price signals and the appropriate incentives to react to those prices in a manner that promotes economic efficiency and the efficient operation of the electricity market.

Texas has long appreciated the value of demand-side market resources. Prior to the full-scale restructuring of the ERCOT market in January 2002, the Electric Reliability Council of Texas (ERCOT) market relied upon roughly 3,500 MW of interruptible load, group load curtailment programs, direct load control, and other load management technologies to maintain reliability and provide a resource to the market. This traditionally high reliance on demand-side resources was largely due to a base of industrial facilities such as petroleum refineries, chemical production facilities, steel mills, and air separation facilities that can interrupt operations at a lower cost than many other types of manufacturing facilities.

As the ERCOT market was redesigned in the 1999 to 2001 period to introduce retail competition and to refine wholesale operations, the preservation of demand-side resources and demand response emerged as a policy objective. The Public Utility

Commission of Texas (PUCT) ordered ERCOT to "Develop new measures and refine existing measures to enable load resources a greater opportunity to participate in the ERCOT market." (PUCT, 2000)

The approach taken in ERCOT to facilitate the development of demand-side resources and demand response has been unique. While other markets have established "stand-alone" programs for demand-side resources (e.g., the emergency curtailment programs established in the New York, PJM, and New England wholesale markets), the ERCOT market rules are designed to encourage demand-side resources and demand response to compete head-to-head against supply-side alternatives. Curtailable and interruptible energy consumers compete in the markets for balancing energy and ancillary services that were initially designed for supply-side resources (i.e., power generation companies).

Has ERCOT succeeded in the establishment of a market that facilitates appropriate responses to price signals? Restructuring has impacted different sectors and technologies distinctly. Direct load control efforts involving residential energy consumers have not successfully made the transition to the new market structure, and thermal energy storage devices have not proven to be economically viable in the new market. However, on a positive note, large industrial chemical and refinery loads with relatively predictable load patterns have prospered under the new market structure, and their interruptibility contributes over 1,600 MW of ancillary services (operating reserves) to the ERCOT market. Due to features of the new market structure, some larger energy consumers who were formerly insulated from wholesale price signals through regulated tariffs are now exposed to market-based wholesale market prices via creative contractual arrangements between retail electric providers and consumers.

When an industrial energy consumer formally offers its *interruptibility* to the ERCOT market as an ancillary service or offers to curtail its usage in order to provide an offset to balancing energy, then the quantity and price of this demand-side resource is known to the market. Thus, it is known with certainty that well over 1,600 MW of demand side resources (interruptible loads) are routinely offering their interruptibility to the ERCOT market as an operating reserve. In addition, anecdotal evidence suggests that many large industrial energy consumers have developed strategies to respond to wholesale prices. As discussed in the following section, ERCOT's market structure provides a variety of incentives to encourage consumers to reduce power purchases during peak or high-price periods. These types of demand response are based on confidential contractual relationships between a retail electric provider (REP) and its large energy consumers and are not announced to the market. This paper attempts to quantify the magnitude of this response in the deregulated ERCOT market.

ERCOT MARKET RULES

ERCOT's market rules provide a variety of possible incentives to encourage industrial energy consumers to respond to wholesale electricity prices. "Voluntary load response" or "passive load response" are terms used to refer to a customer's deviation from its scheduled or anticipated load level in response to price signals in situations where the customer has not formally offered this response to the market as a "resource." How and whether an industrial energy consumer is compensated or credited for responding to price signals is a contractual matter between the customer and its REP.

The energy consumer's qualified scheduling entity (QSE) may earn a credit or payment when the generation it schedules into the market exceeds the generation requirements of the consumers for which it provides scheduling services. While supply-side resources (e.g., power generation plants) are required to follow ERCOT-approved schedules, consumers are free to deviate from scheduled load levels (provided the consumer is not providing an ancillary service). Response to a price signal causes the consumer's QSE to go out of balance, *ceteris paribus*. When a QSE goes "out of balance," a payment or credit to the market is incurred. If a QSE's actual load level turns out to be lower than its scheduled load level during a given 15-minute interval (while its actual generation is equal to its scheduled generation), then the scheduling entity is entitled to a payment or credit, based on the energy imbalance multiplied by the balancing energy market price. This provides loads with an incentive to respond to wholesale market prices, provided the consumer has an arrangement with its REP or QSE to share in the rewards associated with such response.

Some industrial energy consumers rely on balancing energy (essentially, spot market power) to meet some or all of their electricity needs, actively monitor the 15-minute balancing energy prices, and reduce electricity purchases when prices exceed threshold levels. Many REPs will simply pass-through the balancing energy costs, with a small mark-up. QSE’s are not required to schedule the full quantity of their anticipated generation requirements via bilateral contracts with generation companies, and may elect to purchase a share of their generation requirements from the balancing energy market. Many consumers find this strategy of relying on balancing energy to be advantageous, particularly if they possess the capability to reduce energy usage in the face of high market prices. While volatile, balancing energy prices tend to be lower than the cost of firm generation resources obtained via bilateral contracts.

A large industrial energy consumer’s transmission charge is based upon the consumer’s contribution to ERCOT’s coincident peak demand in four summer months of the previous year. Consequently, many consumers actively try to reduce energy consumption during expected peaks. Consultants now offer “4-CP forecasting models,” to assist industrial energy consumers in the avoidance of transmission charges. Often, transmission charges are treated as a “pass-through” cost in the contracts offered by REPs. Consequently, larger energy consumers may see direct benefits by avoiding the four summer peaks. Avoiding transmission charges provides a further incentive for voluntary or passive load response.

If an energy consumer opts to offer its interruptibility into an ancillary services market, then its ability to react to wholesale price signals will be constrained. The load is then relied upon by ERCOT to meet operating reserves needs. If the load is providing responsive reserves (the most popular type of ancillary service provided by industrial interruptible energy consumers), ERCOT will monitor the load’s level every three seconds to ensure that the load is available for interruption should the system need to rely upon the interruption of the load to maintain frequency. Many Houston-area industrial loads are providing ancillary services to the market. Thus many of the Houston area's most flexible, interruptible, or potentially price elastic electric loads will not react to prices. The benefits of maintaining a predictable load level in order to provide an operating reserve outweighs the anticipated benefits that the interruptible energy consumer would realize from reacting to price signals.

Anecdotal evidence suggests that some industrial energy consumers are responding to price signals. However, this magnitude of this behavior has not previously been studied in any rigorous manner.

STATISTICAL ANALYSIS

To further explore and quantify the reaction of participants to changing hourly prices, statistical analysis was performed. Price elasticities, measuring the average responsiveness of the twenty largest Houston-area industrial energy consumers to price changes, are estimated.

The degree of demand response exhibited by an industrial energy consumer may be affected by a variety of factors, including the consumer's flexibility in scheduling production, whether the consumer has committed to providing its interruptibility to the market as an ancillary service, the relative importance of electricity to the consumer, the consumer's other energy options (e.g., using natural gas as a substitute, backup generation, etc.), labor commitments, the magnitude of the price fluctuations, and the firm's daily production goals. In the statistical approach adopted here, electricity consumed in different time periods is treated as different inputs into the participant's production function. The degree to which electricity purchases in different time periods are substitutes (or compliments) is measured empirically.

In developing a model to estimate customer responsiveness to wholesale electricity prices, a short-run daily production function is assumed:

$$Y = G(H(E_1, \ldots ,E_n), \boldsymbol{Z}) \tag{1}$$

Here, production is determined by n various electricity inputs, where the inputs represent purchases of power during different periods of a day. H represents the electricity input function. E_i represents the amount of electricity consumed during time period i. $\boldsymbol{Z}$ is a vector of all other inputs (labor, raw materials, other energy resources, etc.). The production function is designed to describe only the consumer's short-run operating decisions. Production capacity and other capital inputs are assumed to be fixed. Weak separability or zero elasticity of substitution is assumed between the electricity inputs and all other inputs, $\boldsymbol{Z}$. This assumption is necessary because data on the prices and quantities used of these other inputs are not available.

A two-stage decision process is implied here. In the first stage, the industrial energy consumer determines its desired electricity consumption for the day, based upon production goals. In the second stage, the consumer determines how to schedule operations and purchase electricity to meet its daily output target.

The dual concave positively linear homogeneous cost function for the electricity input function may be expressed as:

$$C = c\,(P_1, \ldots, P_n; \boldsymbol{Q}; E^*) \tag{2}$$

C is the total cost of electricity, $\boldsymbol{Q}$ is a vector of exogenous factors affecting demand (e.g., daytype, weather, and natural gas prices). Following, Hirschberg and Aigner (1983) and many other articles in this literature, E^* is used to represent total energy consumed (a proxy for output). $P_1,\ldots,P_n$ denote the prices of the n different electricity inputs. Input levels are endogenous, while the hourly prices are exogenous (determined by the ERCOT market for balancing energy).

The assumption that input prices are exogenous implies that the consumers being modeled do not individually have sufficient market power to significantly affect the balancing energy market prices. The average consumption of each of the electric accounts individually modeled tends to be in the 20 to 75 MW range, while ERCOT’s peak demand is over 59 GW. Further, because binding balancing energy prices are calculated and announced from 10 to 20 minutes in advance of each pricing interval, concerns about an endogenous relationship between demand response and prices are somewhat lessened.[2] The results of a formal Hausman test for exogeneity further suggested that the endogeneity of prices was not a serious concern.[3]

The true underlying cost function for industrial energy consumers may be approximated by a variety of different functional forms. In previous analyses of industrial customer response to time-of-use pricing programs, Chung and Aigner (1981) and Hirschberg and Aigner (1983) used a translog model. Woo (1985) used a Generalized Leontief (GL) function, noting that if the degree of substitutability among inputs is close to zero and the price variation in the sample data is large, then a GL function may be more appropriate than a translog. Alternative functional forms were tested by Hirshberg (1987) for the analysis of time-of-use rate data, and the alternative functional forms provided similar results. A constant elasticity of substitution (CES) model was employed by Caves and Christensen (1984) to study residential customer response.

To analyze industrial customer response to real-time pricing programs, Zarnikau (1990) used a flexible translog function. Although flexible, the translog model often fails to satisfy the concavity property of the underlying cost function at every point. Diewert and Wales (1987) showed that imposition of global concavity in the translog cost

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[2] Some endogeneity between demand changes and prices are still possible, because the demand and price data were aggregated into three-hour blocks. Consequently, it is conceivable that a price change early in the three-hour block could affect a consumer's demand which could cause a change in prices later in the three-hour block. While we do not consider this to be a significant shortcoming, this issue is presently being further examined in a subsequent study.

[3] Using aggregated load for the 20 energy consumers, the test results support the contention that prices are not affected by actions of these customers in the aggregate for all time periods except perhaps the early morning and late evening periods. The modeling of each energy consumer on an individual basis further diminishes this potential endogeneity problem.

function almost always destroys flexibility (i.e., the second order terms turn out to be zero). Goldman, et al (2004) used a CES model to examine customer response to day-ahead price signals in a restructured market.

Diewert and Wales (1987) introduced the Symmetric Generalized McFadden (SGM) functional form, through which concavity can be globally enforced. Thus, the SGM form can introduce an important microeconomic condition that is not often satisfied in applied econometric analysis. Kumbhakar (1990 and 1992) provides example applications. The SGM functional form has seldom been used in the field of energy economics. The notable exceptions are Patrick and Wolak (1997) who used an SGM form in their study of the responsiveness of energy consumers to price signals in the restructured UK electricity market, and Nemoto and Goto (2004) who used an SGM model in an analysis of economies of scope in vertical integration among electric utilities. It should be noted that the global concavity of the SGM comes at a cost, especially when concavity conditions are imposed through re-parameterization and the number of inputs is large. In such a case, the system of demand functions is difficult to estimate, viz., because convergence problems are common. Consequently, using the SGM requires much greater research time and attention.

In an earlier paper, a translog functional form was adopted in an analysis of this dataset (Zarnikau, 2004). The results obtained through a translog cost function were higher than anticipated. Further, the similarity of elasticity estimates across various energy consumers appeared to be suspicious, thus motivating our use of an SGM form here.

The following exposition is developed in Kumbhakar (1990 and 1992). The SGM cost function may be written as:

$$C(.) = g(\boldsymbol{P})E^{*} + \sum_{i} b_i P_i + \sum_{i} b_{ii} P_i E^{*} + \sum_{i} \sum_{j} d_{ij} P_i Q_j E^{*} + \sum_{j} a_j (\sum_{i} \phi_{ij} P_i) Q_j + b_{YY} (\sum_{i} \beta_i P_i) E^{*2}$$
$$+ \sum_{k} \sum_{j} \delta_{kj} (\sum_{i} \lambda_{ijk} P_i) Q_k Q_j E^{*} \qquad (3)$$

Where

$$g(\boldsymbol{P}) = \boldsymbol{P'SP/2\theta'P} \qquad (4)$$

$\boldsymbol{S}$ is an N x N symmetric negative semidefinite (NSD) matrix such that $\boldsymbol{S'}\, \boldsymbol{P}^{*} = 0$ with $\boldsymbol{P}^{*} >> 0$.

The parameters ϕ_{ij}, b_{yy}, and λ_{ijk} are assumed to be exogenously determined, and are therefore not estimated. The remaining parameters are estimated. As noted above, E^{*} represents total daily electricity consumption and is used as a proxy for the firm's output. Variables in the set $\boldsymbol{Q}$ include: CDD (cooling degree days), a measure of weather; NGP, the daily natural gas price; and DAYT, a binary dummy variable with a value of 1 for weekdays. All variables have a daily time frequency, although the time subscript on the variables has been dropped to simplify this presentation.

To ensure that the cost function is globally concave in the input prices, ***S*** must be NSD. This is ensured by reparameterizing ***S*** as ***S*** = -***Γ Γ'*** where ***Γ*** is a lower triangular matrix, the parameters of which are directly estimated.

By Shephard's Lemma ($\delta C / \delta P_i = X_i$), partially differentiating the cost function with respect to the factor prices yields the derived demand functions for the factors of production. This yields:

$$X_i = E^*\{[\boldsymbol{S}^{(i)}\boldsymbol{P}]/(\boldsymbol{\theta}'\boldsymbol{P}) - (\theta_i/2)[\boldsymbol{P}'\boldsymbol{S}\boldsymbol{P}]/(\boldsymbol{\theta}'\boldsymbol{P})^2\} + b_{ii}E^* + b_i + b_{YY}\beta_i E^{*2} + \sum_y d_{ij}Q_j E^*$$

$$+ \sum_j a_j \phi_{ij} Q_j + \sum_k \sum_j \delta_{kj}\lambda_{ijk} Q_j Q_k E^* + \varepsilon \qquad (5)$$

Where ***S' P*** = *0* and ε is a random disturbance term. $\boldsymbol{S}^{(i)}$ is the ith row of the ***S*** matrix. These demand functions are directly estimated.

Daily consumption was modeled as eight three-hour commodities to permit analysis of consumption shifting behavior in response to price fluctuations. Aggregation of the hourly price and consumption data to three-hour periods simplifies the model specification and estimation, and facilitates interpretation of the results.

Following Kumbhakar (1990 and 1992) and Nemoto and Goto (2004) a variety of parameters that are assumed to be exogenous to the system or that cannot be uniquely identified are set equal to the mean of X_i. These parameters are $\theta_i, \phi_{ij}, \beta_i$, and λ_{ijk}. One of the variables in the set $\boldsymbol{Q}$ is a binary dummy variable, namely DAYT. Because $\text{DAYT}^2 = \text{DAYT}$, there is perfect multicollinearity among these two variables. Consequently, the parameter $\delta_{DAYT,DAYT}$ is not estimated.

The demand functions (Eq. 5) for each of the eight three-hour time periods were estimated using Zellner's iterative seemingly unrelated regressors method (which is asymptotically equivalent to a maximum likelihood estimator) using SAS software. The parameters within the matrix $\boldsymbol{\Gamma}$ are shared by the demand functions constructed for each of the eight time periods. In this application, there are 61 model variables, of which 53 are exogenous. There are 141 parameters to be estimated. A variety of plausible parameter restrictions were tested, in order to simplify the model and reduce the number of parameters to be estimated. The restrictions tested include: $b_i = b$, $b_{ii} = b_{xx}$, $b_{yy}\,\beta_y = b_{yyx}$, $d_{ij} = d$, and $a_j\,\phi_{ij} = a_j$. Here the x subscript is used to represent a parameter restriction which renders the parameter constant across different demand equations (periods of time within a day). Unfortunately, these restrictions often led to convergence problems, and were consequently abandoned.

Due to the complexity of the model, the sharing of parameters across demand functions, parameter restrictions within the $\boldsymbol{\Gamma}$ matrix, and the nonlinearities inherent in the model structure, considerable attention was devoted to ensuring successful convergence. Grid searches were conducted to identify candidate starting values. Marquardt's method proved superior to the Gauss-Newton method in the iteration minimization process. In order to achieve convergence, it was necessary to increase the iteration limits, sub-iteration limits, and convergence criteria from the default values used in SAS's Model Procedure. It may be noted that in many of the previous applications of the SGM model described in the literature, fewer inputs were modeled (often, three) so that convergence may not have been as great a challenge. Sturm (1997) reports the need to take some fairly drastic measures to achieve convergence in an SGM model with a much simpler three input case. Since eight inputs are reflected in this modeling, the modeling undertaken here is inherently complex. While Patrick and Wolak (1997) modeled an even greater number of electricity inputs (48), it may be questioned whether their use of Fourier series to reduce the number of parameters estimated and to smooth out the resulting elasticity estimates to address this problem has any theoretical support.

The price elasticity of demand for electricity in period *i* based on a change in the wholesale price of electricity in period *j* is:

$$E_{ij} = \{P_j E^* / X_i\}[s_{ij} / \boldsymbol{\theta}'\boldsymbol{P} - [S^{(i)}\theta_j + S^{(j)}\theta_i]\boldsymbol{P'/\theta'P}]^2 + \theta_i\theta_j[\boldsymbol{P'SP]/(\theta'P}]^3 \tag{6}$$

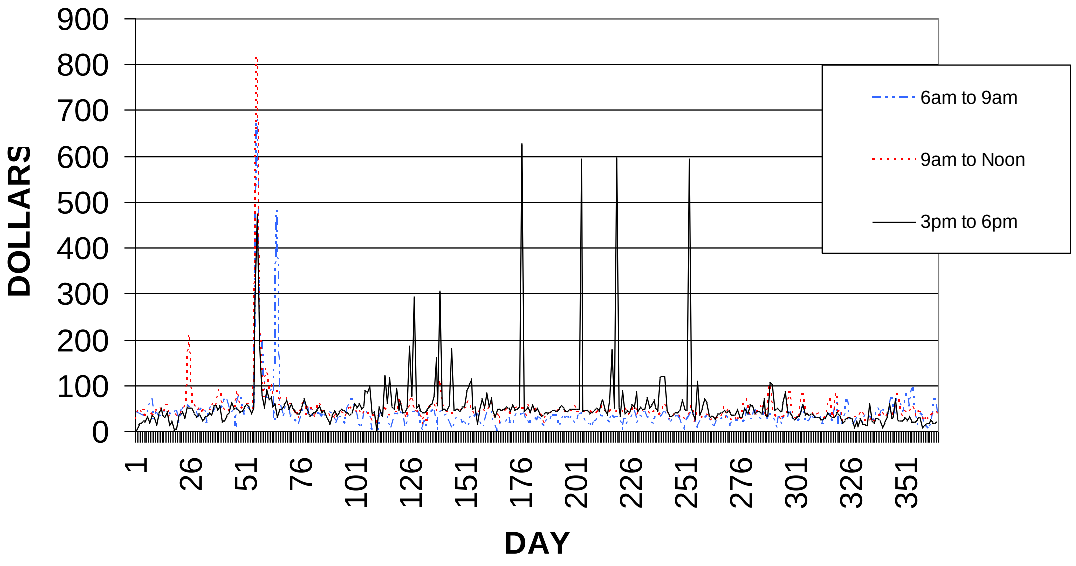
In this paper, elasticities are reported at the mean values of each input vector. Since concavity is imposed globally, the own-price elasticities are negative at each data point. This is hardly the case with other flexible functional forms such as the translog. With the SGM specification we are not imposing global concavity at the cost of flexibility. The SGM cost function is flexible.

DATA SOURCES

Hourly energy consumption data for the twenty largest industrial energy accounts in the Houston area were obtained from CenterPoint Energy, the provider of transmission and distribution services in the Houston area. In many cases, these consumers purchase power through more than one account. Consequently, these data may represent some portion of their total purchases. The actual identity of these energy consumers was not revealed, and no attempt has been made to discover their identity. The hourly data were converted into a time series of energy consumption in each three-hour interval for the year 2003.

The wholesale price (market-clearing price) of electricity in ERCOT's balancing energy market for the Houston Zone in 2003 in dollars per MWh was obtained from ERCOT's web site. The 15-minute data were converted into a time series of the simple average of electricity prices in each three-hour interval. Transmission prices, based on the costs that are assigned to industrial consumers that purchased electricity during the four summer coincident peaks, are added to the balancing energy prices. Figure 1 graphically depicts the resulting price series for three of the most volatile intervals. Prices spiked in late February, when an ice storm moved through North and Central Texas. The short price spikes during the summer months during the late afternoon (3 p.m. to 6 p.m. period) represent the transmission prices.

Figure 1
PRICES BY PERIOD



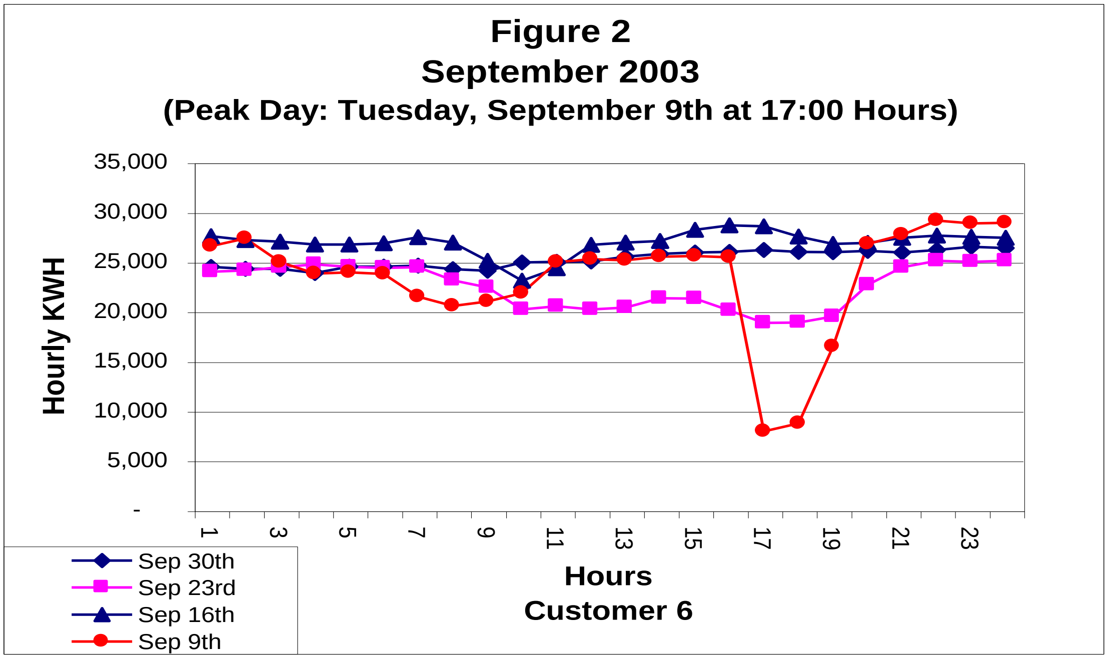
Hourly temperature data for Houston in 2003 were obtained from the National Oceanic and Atmospheric Administration. Cooling degree hours was calculated using a base temperature of 65 degrees F. These data were converted into a time series of cooling degree hours for each three-hour block.

The daily price of natural gas on the NYMEX Exchange in 2003 was also included as a variable, to account for possible fuel switching behavior. Many of the largest industrial energy consumers in the Houston area have cogeneration facilities fueled with natural gas. Thus, it is conceivable that an energy consumer could adjust cogeneration levels and/or switch between electricity and natural gas in order to minimize energy costs. Since only data pertaining to the electricity purchases of these industrial energy consumers is available, "behind the meter" generation can not be easily identified. No negative consumption readings (net exports of power to the grid) were found in the data.

It is not known how many of these energy consumers are providing an ancillary service to ERCOT, and are thus unable to respond to wholesale prices.

RESULTS

Prior to presenting the results from the statistical analysis, it is insightful to graphically examine one consumer's pattern of electricity purchases. There is little doubt that certain energy consumers correctly anticipate and react to price signals. One of the more obvious responses to price signals is depicted in Figure 2, which shows a particular customer's consumption of electricity for the day of the month with one of the four coincident peak periods, as well as the consumer's pattern of electricity consumption for the subsequent three Tuesdays. The customer's purchases of electricity drop off significantly during the summer coincident peak periods used to assign transmission charges. This curtailment is noticeable in relation to other days of the week in the same month and hours before and after the event. Similar patterns were observed in the other three summer months used in the calculation of transmission charges. This is a very obvious case of price response. For other industrial energy consumers in the data set, the responsiveness to price signals is much more subtle.



We first analyzed the price responsiveness of the twenty industrial energy consumers *as a block*. That is, the hourly demand readings for each of the twenty energy consumers were aggregated. It should be noted that the simple correlation between wholesale electricity prices and the quantity of electricity consumed by this group of energy consumers in 2003 (i.e., with no adjustments for exogenous variables and with no model structure) is provided in Table 1. In six of the eight time periods, there is a negative correlation between electricity purchases and wholesale prices. It is interesting to note the positive correlation between prices and the quantity of electricity purchased during the late afternoon (3 p.m. to 6 p.m.) period. This is the period of the highest average prices.

Table 1
Simple Correlation Between Consumption and Prices

	Correlation	Prob rho=0
Midnight-3a.m.	-0.1113	0.0335
3a.m.-6a.m.	-0.2718	<.0001
6a.m.-9a.m.	-0.2642	<.0001
9a.m.-Noon	-0.1542	0.0032
Noon-3p.m.	0.0660	0.2083
3p.m.-6p.m.	0.1316	0.0119
6p.m.-9p.m.	-0.1786	0.0006
9p.m.-Midnight	-0.2495	<.0001

Table 2 presents the estimated price elasticities of demand for this aggregated block of large industrial load, evaluated at the mean of each input vector. As one would expect, the own-price elasticity values (on the main diagonal) are consistently negative. As alternative or substitute inputs to the customer's production function, positive cross-price elasticities between the electricity inputs would generally be expected. Yet, consumption, particularly in adjacent periods, may often be complements. Rigidities in production scheduling within labor shifts may account for some of the negative cross-price elasticity estimates. A mix of negative and positive cross-price elasticities were estimated. Note that since the elasticity matrix is assumed to be symmetric, only the upper triangular portion is shown here. Few of the estimated parameters within the matrix $\boldsymbol{\Gamma}$ upon which these elasticity estimates are based are significantly different from zero. Detailed statistical estimation results are provided in Appendix A-1.

Table 2
Price Elasticity of Demand Estimates from SGM Model:
Aggregated Block of Industrial Load

	Midnight-3a.m.	3a.m.-6a.m.	6a.m.-9a.m.	9a.m.-Noon	Noon-3p.m.	3p.m.-6p.m.	6p.m.-9p.m.	9p.m.-Midnight
Midnight-3a.m.	-0.0011	0.0006	0.0001	0.0003	-0.0012	0.0004	0.0006	0.0002
3a.m.-6a.m.		-0.0016	0.0008	-0.0003	0.0006	-0.0003	0.0005	0.0003
6a.m.-9a.m.			-0.0005	0.0000	0.0003	0.0000	-0.0005	-0.0003
9a.m.-Noon				-0.0002	0.0003	-0.0002	0.0000	0.0000
Noon-3p.m.					-0.0014	0.0003	-0.0002	0.0000
3p.m.-6p.m.						-0.0006	0.0003	0.0000
6p.m.-9p.m.							-0.0010	0.0001
9p.m.-Midnight								-0.0006

Results from the SGM model suggest very limited responsiveness to price changes by this group of industrial energy consumers, in the aggregate.

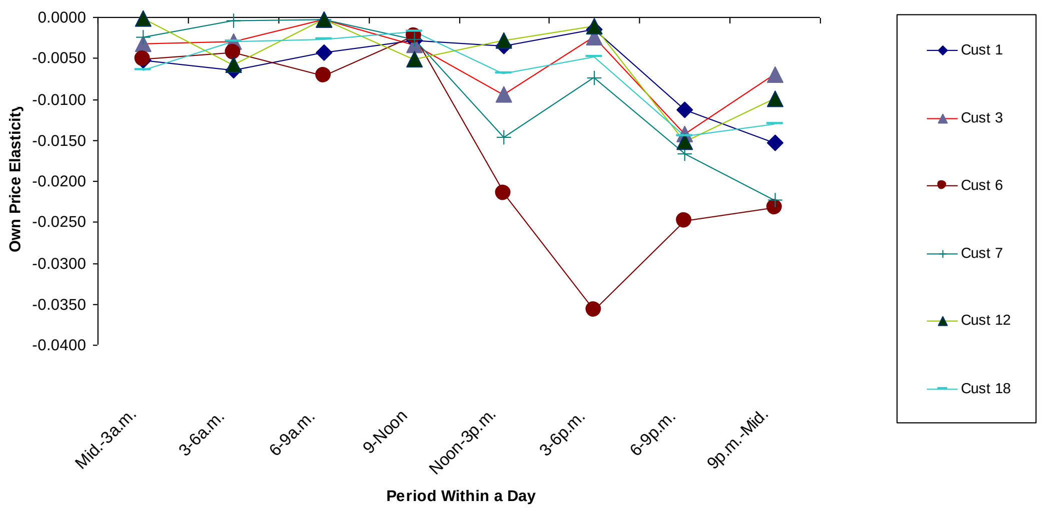
Each customer’s electricity purchasing behavior was also individually analyzed. Because we suspected *a priori* that there would be little similarity among the energy consumer’s response to price changes and little similarity between consumption and the other exogenous variables (weather, daytype, and natural gas prices), we did not employ a panel data approach. Instead, a SGM model was solved for each energy consumer individually. The estimated own-price elasticities are presented in Table 3.

Table 3
Estimated Own-Price Elasticities

Consumer	Mid.-3a.m.	3-6a.m.	6-9a.m.	9-Noon	Noon-3p.m	3-6p.m.	6-9p.m.	9p.m.-Mid.
1	-0.0052	-0.0065	-0.0043	-0.0028	-0.0035	-0.0015	-0.0112	-0.0153
2	-0.0008	-0.0010	-0.0011	-0.0014	-0.0029	-0.0022	-0.0077	-0.0106
3	-0.0032	-0.0029	-0.0002	-0.0034	-0.0094	-0.0025	-0.0143	-0.0069
4	-0.0035	-0.0047	-0.0015	-0.0015	-0.0012	-0.0012	-0.0036	-0.0016
5	-0.0017	-0.0004	-0.0033	-0.0040	-0.0047	-0.0026	-0.0102	-0.0096
6	-0.0050	-0.0043	-0.0071	-0.0022	-0.0215	-0.0357	-0.0248	-0.0232
7	-0.0024	-0.0004	-0.0002	-0.0026	-0.0147	-0.0074	-0.0167	-0.0223
8	-0.0024	-0.0012	-0.0007	-0.0012	-0.0034	-0.0020	-0.0037	-0.0037
9	-0.0031	-0.0019	-0.0009	-0.0040	-0.0063	-0.0020	-0.0069	-0.0068
10	-0.0007	-0.0003	-0.0006	-0.0015	-0.0008	-0.0007	-0.0058	-0.0041
11	-0.0003	-0.0007	-0.0026	-0.0067	-0.0022	-0.0027	-0.0064	-0.0074
12	-0.0002	-0.0058	-0.0003	-0.0052	-0.0028	-0.0010	-0.0152	-0.0099
13	-0.0003	-0.0004	-0.0012	-0.0004	-0.0002	-0.0003	-0.0019	-0.0004
14	-0.0019	-0.0019	-0.0008	-0.0014	-0.0009	-0.0007	-0.0023	-0.0016
15	-0.0008	-0.0032	-0.0005	-0.0005	-0.0016	-0.0022	-0.0038	-0.0036
16	-0.0001	-0.0003	-0.0001	-0.0041	-0.0030	-0.0019	-0.0075	-0.0088
17	-0.0004	-0.0019	-0.0004	-0.0016	-0.0008	-0.0005	-0.0025	-0.0027
18	-0.0064	-0.0029	-0.0027	-0.0017	-0.0068	-0.0049	-0.0145	-0.0130
19	-0.0002	-0.0001	-0.0004	-0.0004	-0.0012	-0.0004	-0.0026	-0.0017
20	-0.0045	-0.0054	-0.0015	-0.0015	-0.0027	-0.0025	-0.0052	-0.0034
AverageValue	-0.0022	-0.0023	-0.0015	-0.0024	-0.0045	-0.0037	-0.0083	-0.0078
Highest Value	-0.0001	-0.0001	-0.0001	-0.0004	-0.0002	-0.0003	-0.0019	-0.0004
Lowest Value	-0.0064	-0.0065	-0.0071	-0.0067	-0.0215	-0.0357	-0.0248	-0.0232

Figure 3 graphically depicts these own-price elasticity values for the six most responsive energy consumers. Indeed, among the twenty largest energy consumers in the Houston area, only a few are exhibiting a pronounced response to price signals. Among this group the most significant response is coming from Customer 6, which is the same energy consumer whose attempt to avoid a summer coincident peak transmission charge was shown in Figure 1. Customer 7 also exhibits some response to wholesale price signals, particularly late in the day. The remainder of this group exhibits relatively little responsiveness to price signals, particularly during the early hours of the day.

Figure 3
Average Elasticities for the Six Most Responsive Energy Consumers



Estimated cross-price elasticity values for each of the 20 energy consumers are provided in Appendix A-2. Typical values are similar to the estimates provided in Table 2 for the group as a whole.

Because the statistical results obtained from the separate analysis of each individual energy consumer are quite voluminous, they will not be presented here, but can be obtained from the author for correspondence. The R^2 statistics were never lower than 0.84, and typically were between 0.94 and 0.98.[4] As might be inferred from the

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[4] In a SGM specification where E* is used as a proxy for output, a high R^2 will, in part, reflect some correlation between demand in the three-hour time period and total demand within the entire day for the consumer.

elasticity results, majority of the elements of the matrix $\boldsymbol{\Gamma}$ for many of the energy consumers were not significantly different from zero at the levels of significance often employed (confirming there was little, if any, significant price response occurring). It might be worth noting here that the parameters of interest are in **S,** but we reparametrized **S** as $\mathbf{S} = -\boldsymbol{\Gamma}\boldsymbol{\Gamma}'$ and estimated the parameters within the matrix $\boldsymbol{\Gamma}$**.** So the estimated standard errors of the parameters in $\boldsymbol{\Gamma}$ may not be of direct interest.

Our rationale for adopting a SGM model over the more common translog alternative was that the econometrics literature warns that translog models may yield unreliable results if prices are volatile and the actual degree of substitution among inputs is limited (see, for example, Woo, 1985). As Patrick and Wolak (1997) note: " . . . imposing the curvature restrictions globally on the translog generally implies implausibly large amounts of substitutability across load periods, and therefore implausibly large own-price elasticities of demand." Running this same data set through the common translog model does indeed provide very different (implausibly high) elasticity results, as can be seen from Table 4. Other recent papers have noted problems with translog functions. Frondel and Schmidt (2002) found the elasticity estimates obtained from translog models to be unreasonably sensitive to the levels of the cost shares associated with various inputs. Using a frequentist non-parametric test for model specification error, Zarnikau (2003) found that the translog model performed poorly in a cross-sectional study of U.S. residential energy consumption. The results presented here would seem to confirm that caution must be exercised when using a translog specification in an application such as this.

Table 4
Price Elasticity of Demand Estimates from Translog Model:
Aggregated Block of Industrial Load

	Midnight-3a.m.	3a.m.-6a.m.	6a.m.-9a.m.	9a.m.-Noon	Noon-3p.m.	3p.m.-6p.m.	6p.m.-9p.m.	9p.m.-Midnight
Midnight-3a.m.	-0.5081	0.2997	0.4177	0.2125	-0.1237	-0.0979	-0.1232	-0.0973
3a.m.-6a.m.		-0.5157	0.4175	0.2551	-0.1394	-0.0552	-0.1384	-0.0500
6a.m.-9a.m.			-0.4107	0.2540	-0.1315	-0.0476	-0.1317	-0.0461
9a.m.-Noon				-0.3658	-0.1451	-0.1117	-0.1426	-0.1021
Noon-3p.m.					-1.7364	0.3681	-0.7122	0.3960
3p.m.-6p.m.						-4.5354	1.8172	-3.5074
6p.m.-9p.m.							-1.7072	0.3743
9p.m.-Midnight								-5.1273

CONCLUSION

In the aggregate, the twenty largest Houston area industrial energy consumers exhibited very little responsiveness to wholesale electricity prices in 2003. Yet, despite the very limited aggregate response, a few of the energy consumers in this group did indeed exhibit a pronounced response to price changes.

The limited responsiveness may not necessarily be evidence of failure in market design. We suspect that some of the industrial energy consumers with the most operational flexibility in this set opted to provide their interruptibility to the ERCOT market as an operating reserve. Once an energy consumer commits to providing an operating reserve, it must follow a predictable load pattern and can no longer chase prices.

It has also been suggested that it may take a few years for industrial facilities to develop strategies to understand and respond to price signals in a restructured market. Perhaps subsequent analysis of voluntary or passive load response among energy consumers in ERCOT in future years will reveal greater price elasticities of demand.

Our results also demonstrate the significant differences in elasticity estimates that can be obtained from SGM versus translog cost equation models, which highlights the dangers in using a translog model in an application involving fairly volatile input prices.

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APPENDIX A-1
RESULTS FROM SGM MODEL ESTIMATION
ESTIMATION OF 20 ENERGY CONSUMERS AS AN AGGREGATE BLOCK

Note: A subscript of A or a indicates the first time period of the day (i.e., midnight to 3 a.m.), B or b indicates the second (i.e., 3 a.m. to 6 a.m.), etc.

Equation	SSE	MSE	Root MSE	R-Square	Adj R-Sq
ENERGYA	2.354E11	6.7729E8	26024.8	0.9645	0.9629
ENERGYB	3.335E11	9.5969E8	30978.9	0.9510	0.9487
ENERGYC	1.544E11	4.4438E8	21080.4	0.9773	0.9762
ENERGYD	1.113E11	3.2032E8	17897.4	0.9848	0.9841
ENERGYE	1.081E11	3.1118E8	17640.3	0.9853	0.9846
ENERGYF	1.5E11	4.3172E8	20777.8	0.9792	0.9783
ENERGYG	2.069E11	5.9553E8	24403.5	0.9695	0.9681
ENERGYH	2.967E11	8.5367E8	29217.7	0.9571	0.9550

Nonlinear ITSUR Parameter Estimates

Parameter	Estimate	Approx Std Err	t Value	Approx Pr > |t|
b_{aa}	0.140096	0.0650	2.16	0.0318
b_{bb}	0.190648	0.0729	2.62	0.0093
b_{cc}	0.195586	0.0504	3.88	0.0001
b_{dd}	0.121589	0.0479	2.54	0.0115
b_{ee}	0.114257	0.0467	2.44	0.0150
b_{ff}	0.093502	0.0540	1.73	0.0840
b_{gg}	0.100556	0.0567	1.77	0.0771
b_{hh}	0.117022	0.0667	1.75	0.0803
b_a	-258917	690313	-0.38	0.7078
b_b	-385909	788996	-0.49	0.6251
b_c	-598872	544557	-1.10	0.2722
b_d	153510.4	507953	0.30	0.7627
b_e	-38187.3	498587	-0.08	0.9390
b_f	318235.2	581806	0.55	0.5847
b_g	177642.8	617976	0.29	0.7739
b_h	-229567	722819	-0.32	0.7510
b_{YYa}	-754E-12	1.503E-9	-0.50	0.6165
b_{YYb}	-2.74E-9	1.643E-9	-1.67	0.0956
b_{YYc}	-1.82E-9	1.138E-9	-1.60	0.1111
b_{YYd}	3.8E-10	1.11E-9	0.34	0.7323
b_{YYe}	1.391E-9	1.081E-9	1.29	0.1992
b_{YYf}	1.183E-9	1.232E-9	0.96	0.3376
b_{YYg}	9.13E-10	1.275E-9	0.72	0.4744
b_{YYh}	-328E-13	1.512E-9	-0.02	0.9827
d_1	-0.00004	0.000178	-0.25	0.8029
d_{b1}	0.000944	0.000162	5.82	<.0001
d_{c1}	0.000268	0.000101	2.65	0.0085
d_{d1}	-0.00017	0.000110	-1.50	0.1337
d_{e1}	-0.00034	0.000104	-3.25	0.0013
d_{f1}	-0.00031	0.000109	-2.84	0.0048
d_{g1}	-0.00034	0.000097	-3.46	0.0006
d_{h1}	-0.00029	0.000137	-2.12	0.0346
d_{a2}	0.003195	0.00615	0.52	0.6039
d_{b2}	0.002721	0.00722	0.38	0.7067
d_{c2}	-0.00358	0.00494	-0.72	0.4694
d_{d2}	-0.00368	0.00432	-0.85	0.3948
d_{e2}	-0.00676	0.00424	-1.59	0.1119
d_{f2}	-0.001	0.00497	-0.20	0.8401
d_{g2}	0.000353	0.00567	0.06	0.9504

d_{h2}	0.006594	0.00676	0.98	0.3299
d_{a3}	0.002405	0.00370	0.65	0.5161
d_{b3}	0.011145	0.00425	2.62	0.0091
d_{c3}	0.001942	0.00291	0.67	0.5044
d_{d3}	-0.00071	0.00262	-0.27	0.7853
d_{e3}	-0.00579	0.00257	-2.25	0.0250
d_{f3}	-0.00564	0.00295	-1.91	0.0567
d_{g3}	-0.00802	0.00333	-2.41	0.0165
d_{h3}	-0.0047	0.00400	-1.17	0.2413
AA1	1731.448	2819.4	0.61	0.5395
AB1	-12312.3	2670.7	-4.61	<.0001
AC1	-3648.1	1653.4	-2.21	0.0280
AD1	3820.364	1810.7	2.11	0.0356
AE1	4321.423	1736.1	2.49	0.0133
AF1	2723.082	1895.4	1.44	0.1517
AG1	3596.269	1639.0	2.19	0.0289
AH1	2399.968	2165.1	1.11	0.2684
AA2	20421.59	71567.7	0.29	0.7755
AB2	-37383.1	82988.0	-0.45	0.6527
AC2	29385.05	57315.9	0.51	0.6085
AD2	-19129.4	52445.9	-0.36	0.7155
AE2	56242.83	51775.7	1.09	0.2781
AF2	-19291.3	60796.6	-0.32	0.7512
AG2	2807.988	65574.0	0.04	0.9659
AH2	31711.64	76752.2	0.41	0.6797
AA3	-48658.1	53830.5	-0.90	0.3667
AB3	-170644	60622.0	-2.81	0.0052
AC3	-30755.9	41791.5	-0.74	0.4623
AD3	21126.38	38901.3	0.54	0.5874
AE3	102770.9	38832.5	2.65	0.0085
AF3	108285.8	43958.9	2.46	0.0142
AG3	77716.63	48007.7	1.62	0.1064
AH3	91448.29	57525.3	1.59	0.1128
δ11a	-1.61E-7	4.11E-7	-0.39	0.6954
δ11b	-5.08E-7	3.93E-7	-1.29	0.1971
δ11c	1.84E-7	2.405E-7	0.77	0.4448
δ11d	5.361E-7	2.508E-7	2.14	0.0332
δ11e	3.381E-8	2.473E-7	0.14	0.8913
δ11f	-2.28E-7	2.682E-7	-0.85	0.3953
δ11g	2.941E-7	2.472E-7	1.19	0.2350
δ11h	5.933E-7	3.317E-7	1.79	0.0745
δ12a	-3.33E-6	5.425E-6	-0.61	0.5391
δ12b	-0.00002	5.403E-6	-3.68	0.0003
δ12c	-6.53E-6	3.491E-6	-1.87	0.0621
δ12d	-6.56E-6	4.059E-6	-1.62	0.1069
δ12e	7.902E-6	4.039E-6	1.96	0.0512
δ12f	0.000014	4.55E-6	3.00	0.0029
δ12g	0.00001	3.748E-6	2.74	0.0065
δ12h	0.000012	4.354E-6	2.65	0.0084
δ13a	-2.18E-6	5.445E-6	-0.40	0.6893
δ13b	-0.00001	5.287E-6	-2.47	0.0141
δ13c	2.595E-6	3.303E-6	0.79	0.4327
δ13d	3.998E-6	3.642E-6	1.10	0.2731
δ13e	7.324E-6	3.646E-6	2.01	0.0453
δ13f	8.446E-6	3.836E-6	2.20	0.0283
δ13g	2.105E-6	3.348E-6	0.63	0.5299
δ13h	7.167E-6	4.476E-6	1.60	0.1102
δ22a	-0.00038	0.000447	-0.84	0.3995
δ22b	0.000011	0.000528	0.02	0.9828
δ22d	0.000175	0.000361	0.49	0.6279
δ22d	0.000467	0.000310	1.51	0.1327
δ22e	0.000283	0.000305	0.93	0.3546
δ22f	0.000161	0.000359	0.45	0.6543
δ22g	-0.00013	0.000416	-0.31	0.7581
δ22h	-0.00079	0.000499	-1.58	0.1150
δ23a	-0.00007	0.000222	-0.30	0.7608
δ23b	-0.00018	0.000263	-0.68	0.4976
δ23c	0.000017	0.000180	0.10	0.9233

δ23d	0.000059	0.000154	0.38	0.7016
δ23e	0.000061	0.000153	0.40	0.6897
δ23f	-1.07E-6	0.000179	-0.01	0.9952
δ23g	0.000263	0.000209	1.26	0.2077
δ23h	-0.00019	0.000249	-0.75	0.4559
r11	53.27524	33.0640	1.61	0.1080
r21	-33.2358	46.2245	-0.72	0.4726
r22	63.58302	18.8169	3.38	0.0008
r31	-5.13458	33.1256	-0.16	0.8769
r32	-32.2771	20.8803	-1.55	0.1231
r33	-5.66201	108.3	-0.05	0.9583
r41	-11.0356	39.8754	-0.28	0.7821
r42	1.713207	27.1151	0.06	0.9497
r43	-9.47463	340.7	-0.03	0.9778
r44	-2.49003	1446.8	-0.00	0.9986
r51	39.08058	42.5505	0.92	0.3590
r52	4.463554	34.7220	0.13	0.8978
r53	19.97932	435.0	0.05	0.9634
r54	-6.90953	8043.5	-0.00	0.9993
r55	5.078769	12320.3	0.00	0.9997
r61	-11.3921	22.5025	-0.51	0.6130
r62	2.4111	16.5886	0.15	0.8845
r63	-15.3879	344.0	-0.04	0.9643
r64	2.116883	4306.4	0.00	0.9996
r65	0.595398	12701.4	0.00	1.0000
r66	19.31556	1093.6	0.02	0.9859
r71	-22.5969	36.2001	-0.62	0.5329
r72	-26.3042	25.7860	-1.02	0.3084
r73	20.00317	434.7	0.05	0.9633
r74	-7.35331	8193.9	-0.00	0.9993
r75	-10.4182	50132.0	-0.00	0.9998
r76	3.822409	11633.2	0.00	0.9997
r77	2.701028	233724	0.00	1.0000

Table A-2
Estimated Cross-Price Elasticities

Consumer	ETAAB	ETAAC	ETAAD	ETAAE	ETAAF	ETAAG	ETAAH	ETABC	ETABD	ETABE	ETABF	ETABG	EGABH
1	0.0036	-0.0015	0.0013	-0.0009	0.0007	0.0035	-0.0012	0.0027	0.0014	-0.0029	-0.0008	0.0006	0.0022
2	0.0003	0.0000	-0.0011	-0.0005	0.0010	0.0009	0.0003	0.0010	0.0007	0.0011	0.0003	-0.0018	-0.0003
3	-0.0005	0.0011	0.0026	-0.0011	-0.0006	0.0005	0.0019	0.0002	0.0003	0.0050	-0.0032	0.0020	0.0011
4	0.0036	-0.0013	-0.0016	0.0008	-0.0010	0.0031	-0.0009	0.0016	0.0020	-0.0011	0.0012	-0.0038	0.0013
5	0.0007	0.0020	-0.0025	0.0005	-0.0006	0.0001	0.0009	-0.0009	0.0012	-0.0005	0.0003	-0.0005	0.0000
6	-0.0006	0.0053	-0.0012	-0.0035	-0.0013	0.0004	0.0056	0.0006	-0.0019	0.0075	-0.0137	0.0081	0.0052
7	-0.0002	0.0002	-0.0007	-0.0018	0.0006	0.0019	0.0030	-0.0003	0.0000	0.0014	-0.0017	0.0017	-0.0002
8	0.0005	-0.0009	0.0002	0.0005	0.0004	0.0024	0.0002	0.0003	0.0011	0.0012	-0.0006	-0.0015	0.0003
9	0.0019	0.0010	0.0007	-0.0045	0.0016	-0.0008	0.0025	-0.0005	0.0008	0.0031	-0.0018	-0.0001	-0.0013
10	-0.0001	0.0005	-0.0010	-0.0001	-0.0003	0.0010	0.0008	0.0001	-0.0002	0.0000	-0.0003	0.0002	0.0006
11	-0.0001	0.0003	0.0007	0.0006	-0.0002	-0.0004	-0.0004	0.0014	-0.0020	-0.0001	0.0008	-0.0006	0.0013
12	-0.0004	0.0002	0.0006	-0.0004	0.0002	0.0002	0.0000	0.0013	-0.0021	0.0019	-0.0014	0.0081	0.0020
13	-0.0002	0.0005	0.0002	-0.0002	0.0002	0.0002	-0.0003	0.0008	0.0000	-0.0003	0.0000	0.0007	-0.0004
14	0.0015	0.0000	-0.0010	0.0002	0.0008	-0.0004	0.0007	0.0005	0.0010	-0.0006	-0.0003	0.0007	-0.0007
15	0.0013	-0.0001	0.0000	-0.0007	-0.0001	0.0002	-0.0006	0.0004	0.0003	0.0012	0.0006	-0.0004	0.0010
16	-0.0002	0.0000	-0.0003	0.0001	0.0001	-0.0004	0.0007	0.0001	-0.0005	0.0002	0.0002	-0.0007	0.0013
17	0.0007	-0.0003	-0.0006	0.0004	0.0000	-0.0001	0.0000	0.0007	0.0019	-0.0011	0.0001	0.0006	-0.0004
18	0.0036	0.0041	0.0006	-0.0042	0.0013	0.0027	-0.0026	-0.0028	0.0000	0.0030	-0.0002	-0.0006	0.0004
19	-0.0001	-0.0001	0.0003	-0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	-0.0001	-0.0001	0.0001	0.0002
20	0.0039	0.0010	-0.0009	-0.0026	0.0008	0.0001	0.0008	0.0001	0.0002	0.0030	0.0008	-0.0008	-0.0003
AverageValue	0.0010	0.0006	-0.0002	-0.0009	0.0002	0.0008	0.0006	0.0004	0.0002	0.0011	-0.0010	0.0006	0.0007
Highest Value	0.0039	0.0053	0.0026	0.0008	0.0016	0.0035	0.0056	0.0027	0.0020	0.0075	0.0012	0.0081	0.0052
Lowest Value	-0.0006	-0.0015	-0.0025	-0.0045	-0.0013	-0.0008	-0.0026	-0.0028	-0.0021	-0.0029	-0.0137	-0.0038	-0.0013

Note: In the column headings, A = Midnight to 3 a.m.; B = 3 a.m. to 6 a.m.; C = 6 a.m. to 9 a.m.; etc.
For example, ETAAH represents the cross-price elasticity between period A (Midnight to 3 a.m.) and period H (9 p.m. to Midnight).
The cross-price elasticity matrix is symmetric. Consequently, ETABG = ETAGB, for example.

Table A-2
Estimated Cross-Price Elasticities

Consumer	ETACD	ETACE	ETACF	ETACG	ETACH	ETADE	ETADF	ETADG	ETADH	ETAEF	ETAEG	ETAEH	ETAFG	ETAFH	ETAGH
1	-0.0020	0.0008	0.0016	-0.0006	0.0035	0.0014	0.0004	-0.0027	0.0021	-0.0001	0.0021	0.0016	-0.0005	-0.0005	0.0073
2	-0.0001	-0.0004	-0.0006	0.0015	-0.0006	-0.0006	0.0009	0.0011	0.0003	-0.0005	-0.0013	0.0040	0.0002	0.0006	0.0062
3	-0.0011	0.0003	0.0000	0.0003	-0.0007	0.0020	-0.0005	-0.0007	0.0010	0.0028	0.0032	-0.0024	0.0028	0.0005	0.0055
4	-0.0004	-0.0001	-0.0004	0.0015	0.0000	0.0004	-0.0003	0.0009	-0.0004	0.0001	0.0000	0.0003	0.0007	-0.0002	0.0007
5	0.0035	-0.0010	0.0018	0.0007	-0.0019	0.0024	-0.0011	0.0003	-0.0002	0.0005	-0.0014	0.0034	0.0019	-0.0007	0.0077
6	0.0011	0.0091	-0.0015	-0.0047	-0.0013	0.0024	-0.0006	0.0018	0.0006	0.0199	-0.0029	-0.0075	0.0127	0.0132	0.0082
7	0.0001	0.0014	-0.0013	0.0012	-0.0011	-0.0038	0.0015	0.0011	0.0037	0.0054	0.0006	0.0095	0.0019	0.0005	0.0073
8	-0.0002	0.0008	-0.0002	0.0015	-0.0003	-0.0005	0.0000	0.0009	-0.0005	0.0015	-0.0015	0.0013	0.0000	0.0005	0.0019
9	-0.0008	0.0009	0.0000	0.0012	-0.0010	0.0004	0.0003	0.0028	-0.0005	0.0016	0.0004	0.0028	-0.0010	0.0008	0.0033
10	0.0004	-0.0002	0.0001	-0.0001	0.0000	-0.0006	-0.0003	0.0017	0.0012	-0.0003	0.0013	0.0004	0.0009	0.0005	0.0008
11	0.0036	-0.0008	-0.0006	0.0005	-0.0018	-0.0005	0.0014	0.0003	0.0030	0.0016	-0.0004	0.0017	0.0015	-0.0015	0.0048
12	0.0001	-0.0001	-0.0001	-0.0010	-0.0003	0.0034	-0.0017	0.0029	0.0016	0.0013	-0.0020	-0.0007	0.0008	0.0011	0.0055
13	0.0002	0.0005	0.0002	-0.0014	0.0008	-0.0001	-0.0004	0.0006	-0.0001	-0.0001	0.0005	-0.0002	0.0005	0.0000	0.0006
14	-0.0003	0.0001	-0.0002	0.0002	0.0003	-0.0001	0.0003	0.0006	0.0004	0.0002	0.0003	0.0003	-0.0001	-0.0002	0.0006
15	-0.0001	-0.0004	-0.0002	0.0005	0.0000	0.0002	-0.0003	-0.0001	0.0000	0.0001	0.0005	0.0002	0.0007	0.0006	0.0018
16	-0.0002	0.0001	0.0001	0.0005	-0.0005	-0.0017	0.0024	0.0029	0.0015	0.0010	0.0012	0.0018	-0.0011	-0.0005	0.0045
17	-0.0005	0.0005	0.0001	-0.0001	-0.0002	0.0004	-0.0002	-0.0003	0.0005	-0.0003	0.0002	0.0004	0.0000	0.0004	0.0017
18	-0.0009	0.0022	-0.0021	-0.0007	0.0030	-0.0006	-0.0017	0.0000	0.0029	0.0003	0.0057	-0.0010	0.0010	0.0038	0.0049
19	0.0003	0.0004	0.0001	-0.0002	-0.0001	-0.0003	0.0000	0.0001	-0.0001	0.0006	0.0010	-0.0002	-0.0004	0.0001	0.0017
20	0.0006	0.0003	-0.0011	0.0004	-0.0006	0.0001	0.0005	-0.0002	0.0004	0.0004	0.0001	0.0001	0.0012	-0.0009	0.0031
	0.0002	0.0127	-0.0002	0.0000	-0.0001	0.0002	0.0000	0.0007	0.0009	0.0018	0.0004	0.0008	0.0012	0.0009	0.0039
	0.0036	0.0091	0.0018	0.0015	0.0035	0.0034	0.0024	0.0029	0.0037	0.0199	0.0057	0.0095	0.0127	0.0132	0.0082
	-0.0020	-0.0010	-0.0021	-0.0047	-0.0019	-0.0038	-0.0017	-0.0027	-0.0005	-0.0005	-0.0029	-0.0075	-0.0011	-0.0015	0.0006

Note: In the column headings, A = Midnight to 3 a.m.; B = 3 a.m. to 6 a.m.; C = 6 a.m. to 9 a.m.; etc.
For example, ETAAH represents the cross-price elasticity between period A (Midnight to 3 a.m.) and period H (9 p.m. to Midnight).
The cross-price elasticity matrix is symmetric. Consequently, ETABG = ETAGB, for example.