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THE EFFECTS OF TIME-OF-USE ELECTRICITY RATES

ON

NEW YORK DAIRY FARMS

by

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ABSTRACT*

Recent concern among New York dairy farmers has grown regarding potential increases in energy costs as upstate utilities, under mandate from the New York Public Service Commission, move to time-of-use electricity rates. Furthermore, since it is often desirable to maintain relatively fixed intervals between daily milkings, farmers have expressed further concern about their ability to shift electricity consumption from expensive peak period hours to relatively inexpensive off-peak hours.

To determine the effects of time-of-use electricity rates on New York dairy farms and to gain a better understanding of methods farmers can adopt to save energy, an empirical model estimating the time-of-day demand for electricity is developed. The parameters from this model are used to simulate load curves for a sample of farms. The time-of-use rates for four upstate utilities are used in conjunction with these load curves to estimate electricity costs under time-of-use and flat rates. Farm characteristics are regressed on the percentage change in the electricity bills for this sample of farms to derive relationships to explain how to reschedule dairy operations to reduce electricity costs under time-of-use rates.

The empirical results indicate that electricity bills will fall for the majority of farms in the move to time-of-use electricity rates. Savings are an increasing function of farm size since larger farms can more easily spread the higher customer charge that accompanies time-of-use rates. There appear to be few incentives for farmers to reschedule dairy operations to realize additional savings under time-of-use pricing.

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THE EFFECTS OF TIME-OF-USE ELECTRICITY RATES ON NEW YORK DAIRY FARMS

1. INTRODUCTION

Over the past 25 years, the electric utility industry has experienced a drastic transformation in its cost structure, caused predominantly by the changing economic climate, by the OPEC oil embargoes of the early 1970's, and by increased environmental and safety concerns in the supply of electric power. Taken together, these factors have lead to substantial increases in the cost to produce and distribute electricity. Combined with increased emphasis on energy conservation and competition from private cogeneration, many utilities have implemented a number of demand side management (DSM) to help keep supply in balance with demand. These DSM programs are designed to contain the growth of demand and are in stark contrast to the utilities' historical emphasis on capacity expansion.

DSM initiatives include conservation programs, incentives to purchase energy efficient equipment and appliances, and innovative pricing such as time-of-use (TOU) rates. TOU rates are the practical application of marginal cost pricing.[1] When compared with the flat rates, used currently by many utilities, and which set the price of electricity based primarily on the average cost of production, time-of-use rates set the price closer to the true marginal cost. Thus, TOU rates give consumers an incentive to reduce electricity consumption during the high-cost peak periods, and/or shift this consumption to the lower cost off-peak periods. In this way, consumers are given the proper price signals needed for their consumption decisions. Although many of these rates are being designed for specific customer classes and are to be revenue neutral,[2] some customers within the class will experience decreases in their electric bills while others will end up paying more. How a customer's bill will change depends on his/her pattern of electricity consumption throughout the day and/or season of the year.

Under order of the New York Public Service Commission (Order 88-23), most utilities throughout New York State are in the process of implementing time-of-use rates for their larger residential customers. One important group of customers that falls under this mandate are dairy

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[1]For simplicity, the terms time-of-use (TOU), and time-of-day (TOD) are used interchangeably throughout this report.

[2]To be revenue neutral, rates are to be set to generate the same total revenue from the customer classes.

farmers.[3] Electricity is a significant input on most dairy farms, comprising around five percent of cash costs (Niagara Mohawk Power Corporation). The major uses are to cool milk, heat water clean equipment, run milking vacuum pumps, and light and ventilate herd housing structures.

Since the distribution of electricity use throughout the day on the dairy farm is dependent on its fixed milking schedule, many dairy farmers have expressed concern that TOU rates will affect them adversely by increasing their electric bills. The concern was great enough that the farm community gathered support from state legislators to amend the Public Service Law to exempt farmers from TOU electricity rates. Although this legislation was never passed, the proposed amendments were based on the premise that farmers have no real flexibility in shifting the time at which they use electric power.

Regardless of the inflexibility of scheduling of dairy farm operations, the extent to which farmers would be adversely affected depends on the rate structure as well as the times of day that a particular utility is at peak load. The magnitude of the effects of these TOU rates will differ by utility and by individual farm characteristics. For this reason, and the fact that agriculture is an important component of many rural economies in New York State, it is important to understand the financial effects on farms of moving to time-of-use rates.

The purpose of this report is to quantify the effects of moving New York dairy farms from flat rates to time-of-use rates. Emphasis is given to the differences in the structure of the TOU rates for four major upstate electric utilities. Particular attention is also given to quantifying the importance of farm size and milking technology. Finally, by estimating the electricity consumption at peak and off-peak periods, some judgement can be made regarding the possibility of reducing electric bills by shifting energy use to off-peak periods.

The data requirements to meet the study's objectives are extensive. One needs data on electricity consumption of the farm, separate from any household demand, energy consumption by major end use (e.g. feeding, milking, milk cooling etc.), and the distribution of energy consumption by season and time of day.

To our knowledge, no such comprehensive data set is available for farms located in New York State, but several years ago, the Department of Agricultural Economics at Cornell University, in cooperation with Niagara Mohawk Power Corporation and the New York State

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[3]Farm operations that have a household on the premises are generally classified under a residential rate category, unless the household and the dairy buildings are metered separately. Consequently, most family farms would be in a residential rate category.

Statistical Reporting Service, conducted two extensive surveys on energy use in agriculture. These two data sets, along with a third data set available from the Midwest, provide the information necessary to conduct an evaluation of TOU rates. These data sets are described below as they are needed.

To accomplish the study's objectives, the remainder of the report is organized into five sections. The next section examines the theory of time-of-use rates and the economic rationale for their use. Section 3 contains estimates of conditional electricity demands for rural households and for dairy farm operations, while section 4 contains a cubic spline regression model for distributing farm electricity demand by time-of-day and season. The focus of section 5 is on simulating electricity load curves for a sample of New York dairy farms from the 1987 survey. Then, the different time-of-use rates either currently in force or being considered by the major upstate New York utilities are applied to these load curves to determine how dairy farms served by different utilities would be affected financially by moving to TOU rates. The final section contains a summary of the empirical findings, along with some policy implications and recommendations for further research.

2. ECONOMIC RATIONALE FOR TIME-OF-USE PRICING

The purpose of this section is to describe in detail the sound economic rationale for why electric utilities around the country have begun to adopt time-of-use pricing.[4] To understand why such rates have not been adopted until now, one must examine the historical characteristics of the industry that led to government regulation in the first place. We begin with a brief background of the evolution of the electric utility industry and then move on to describe the main characteristics that the industry exhibited through the mid 1960's. The major events and the slowdown in the technological progress of the late 1960's that made time-of-use rates feasible are then discussed. Finally, a model of marginal cost pricing, including a derivation of what costs should be included in the price, is developed.

History of the Electric Utility Industry

It wasn't until the latter part of the nineteenth century that it was technically feasible to distribute electricity commercially. Utilities were formed, each having the potential to supply

[4]Much of this background material was taken out of Vennard's *Management of the Electric Energy Business* and Kahn's *The Economics of Regulation.*

electricity to a few square miles at most. During this period these new electric companies were in competition with one another and also previously established gas companies. Government officials believed that by allowing competition, prices would naturally seek levels that reflected the true cost to deliver a unit of electricity. Eventually the stronger and larger firms were able to take advantage of economies of size and began to acquire the weaker, smaller ones. This led to larger electric utilities that more or less controlled all the electricity distribution facilities for an entire area.

Although less competitive, there was a distinct advantage in having one firm supply the electricity for a given area: there was no longer the need for duplication of distribution and transmission systems. In the earliest days of electric companies, during which time competition was promoted, it was not uncommon to have a large number of companies providing electricity for one small area. Consequently, each utility needed to string its own distribution wires. This duplication of capital led to urban blight and increases in the cost of electricity which were passed on in the form of higher prices. Clearly, it was in the public interest to allow these monopolies to exist. Industries in which it is less costly for one firm to supply a good or service as opposed to many are known as natural monopolies (Kahn, 1988). Most utilities, whether electricity, gas, telephone, or cable TV, are classified as natural monopolies.

As the industry became less competitive and the monopolistic firms took advantage of their power, the need for price ceilings and regulations regarding quality of service became apparent. For this reason, many states established public service commissions that were responsible for the monitoring of public utilities. New York and Wisconsin were the first to establish them in 1907 (Vennard, 1979, p. 288).

Since their establishment, public service commissions have played a significant role in setting electricity rates. This is especially true prior to the mid-1960's, when the long-run average cost to produce a unit of electricity was decreasing, implying that the marginal cost curve is everywhere below the average cost curve. The role of regulation, i.e. public service commissions, is to set the price of electricity at average costs to insure an adequate rate of return (see point A of figure 2.1). Without such regulation, natural monopolies would equate marginal revenues to marginal costs, reducing demand and leading to monopoly profits (see point B of figure 2.1).

It is generally agreed that there are three factors that cause firms to exhibit decreasing costs (Kahn, 1988, p.124). All three of these have typified electric utilities from the early 1900's through the mid-1960's.

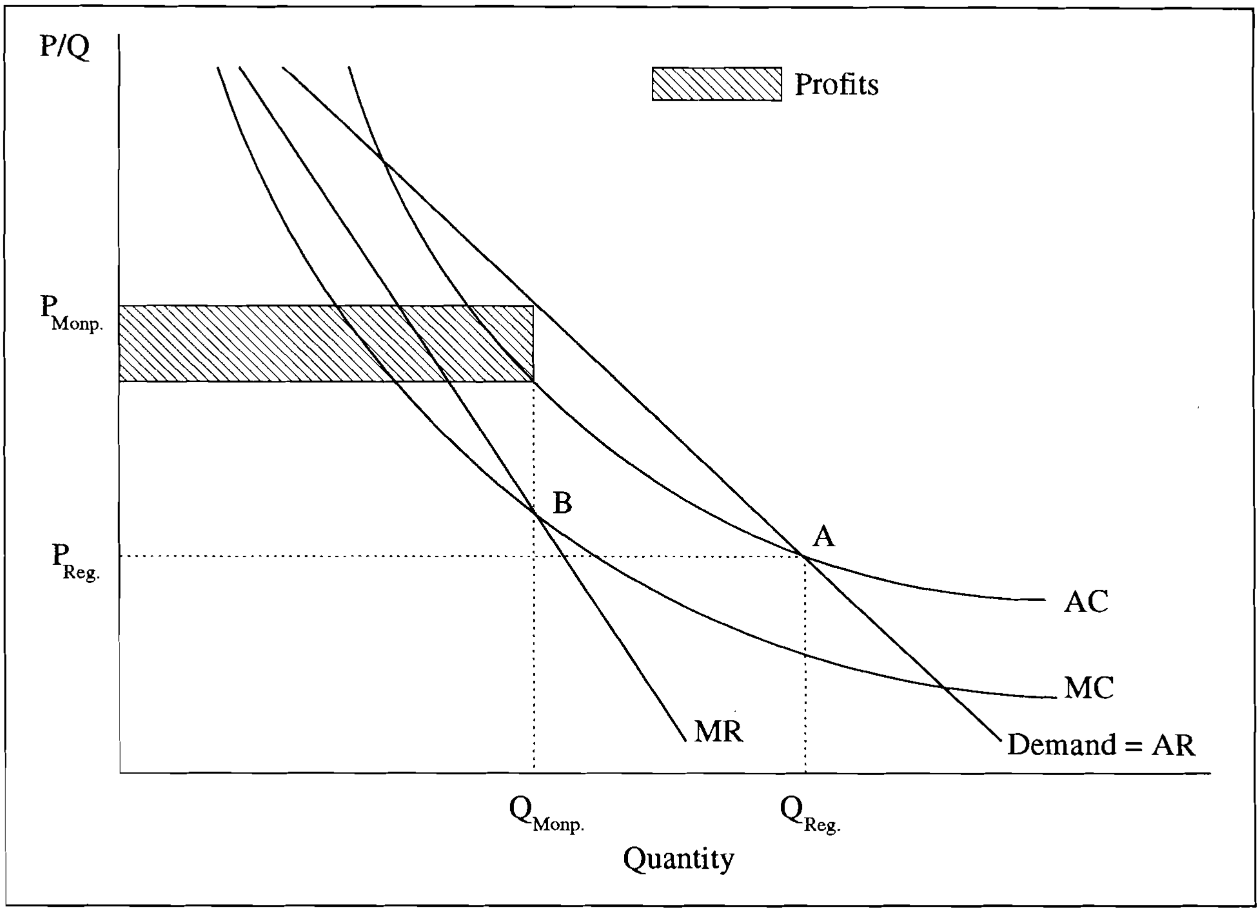

Figure 2.1 Marginal cost (MC), marginal revenue (MR), average cost (AC), and average revenue (AR) curves facing a decreasing cost industry.

The short-run average costs decreased as a result of using existing capacity more extensively. As more and more customers were serviced with electricity, through rural electrification or mandates established by public service commissions, fixed costs were spread over a larger volume. With such a large proportion of fixed costs, any increase in the average variable costs was offset by the decline in average fixed cost, thereby leading to declining short-run average total costs. The fact that utilities have short-run decreasing costs was a primary rationale behind the implementation of decreasing block rates.[5]

The second factor, although not nearly as pronounced as short-run decreasing costs, are long-run decreasing costs. As larger plants and transmission systems were constructed, the cost per unit of electricity decreased. In the generating phase, larger plants operated at higher

[5]Decreasing block rates set the per unit price for electricity successively lower for each block of electricity the consumer uses. They are intended to reflect a short-run decreasing cost function (Vennard, p. 270).

temperatures, leading to greater efficiency in converting primary fuels into electrical energy. In addition, the adaptation of higher voltage transmission lines allowed electricity to be carried farther distances with relatively little power loss. As a result, neighboring utilities joined together and formed power pools to make better use of their baseload plants by pooling any excess electricity generated during off-peak hours and selling to utilities that were currently in peak periods.

Advancements in technology also contributed to decreasing costs. Traditionally, decreases in average total cost due to technological improvements have not been considered a situation of decreasing costs. Technical improvements represent a downward shift in cost curves, not a decrease in average total cost due to producing more. However, many argue that technological improvements induced by higher levels of demand should be considered a situation of decreasing cost (Kahn, 1988, p.127).

There have been numerous examples of technological improvements in the electric industry. Perhaps the most significant advancement was the development of nuclear power. In the beginning, these large plants took advantage of the relatively inexpensive fuels, uranium and plutonium. Advances in technology also lead to the construction of more efficient fossil fuel plants. In 1910, for example, a typical coal-fired plant required about five pounds of coal to produce a Kwh, today this figure is closer to one (Vennard, 1979, p.105).

More recently, the average cost of electricity has escalated dramatically. Vennard (1979, p.96) cites a number of reasons, the most prominent being the fact that improvements in generating efficiency and other areas of electricity production could not keep pace with the higher inflation rates of the late 1960's. These inflation rates pushed up interest rates, which greatly increased the investment costs per kilowatt of new capacity. As a result, the expected yields for bonds and stocks also rose. Investor-owned utilities needed high rates of return in order to attract capital funds to build new plants. Recognizing the need for increased rates of return, government regulators, throughout this period, frequently approved rate increases requested by utilities.

The early 1970's also marked a time when governments, in response to lobbying efforts and public concern, began to enact new safety and environmental standards. Utilities were required to meet emissions standards either by purchasing higher grade fuels or by installing higher smokestacks, etc. These regulations led to long delays and subsequent cost overruns of bringing new capacity on line, particularly nuclear capacity. Again, the only way to account for these additional expenses and sustain the rate of return was to increase the price of electricity.

Besides capacity, the other major cost faced by utilities is for fuel. Due to a high reliance on oil and natural gas, the OPEC oil embargoes led to higher electricity prices throughout the 1970's. Although the real price of oil has declined substantially since then, studies do indicate that oil reserves may be depleted sometime in the early 21st century (Vennard, 1979, p.27).

As a result of these changes over the past 25 years, many agree that the electric utility industry no longer exhibits decreasing costs. Thus, much of the rationale for the historical reliance on average cost pricing no longer applies and marginal cost pricing is a much more viable option.

Marginal Cost Pricing Applied to Electric Utilities

From a utility's perspective, a unit of electricity produced at one time of the day is not the same as a unit produced at some other time. The utilities' system load is constantly changing throughout the day, requiring different plants to come on line and others to go off line. To operate the plants in the least-expensive way, utilities bring on line successively less efficient plants as demand rises during peak periods. This efficiency is measured mainly by the marginal energy costs to produce a unit of electricity, and the short-run marginal cost of the system at any particular moment is the marginal cost to operate the most recent plant (least efficient) to come on line. Thus, the cost to produce electricity varies throughout the day and rates must be structured accordingly.

Besides these short-run marginal costs, or energy costs as they are often called, there are also two other major cost components. First is the cost to meter customers, provide distribution and transmission facilities, and perform other administrative tasks. For the most part, these costs are invariant with the quantity of electricity a customer uses. Utilities often spread these costs evenly among the customers in what is known as a customer charge. The second major cost is that of new capacity. With population increasing and new electricity-using appliances constantly being developed, capacity limitations will continue to be of some concern to some utilities. To complicate matters, many power plants are becoming obsolete and will require replacement by newer, more efficient plants. The additional costs due to expanding capacity, along with the short-run energy costs, make up the long-run marginal costs of providing electricity.

To obtain the most efficient use of resources, the price of a good should be equated with its marginal cost of production, and it seems only logical that regulators should require utilities to practice marginal cost pricing. However, should a utility set prices according to short-run or long-run marginal cost?

To answer the question, we expand on a model initially developed in Munasinghe's *Electric Power Economics*. Although over-simplified, the results form the basis for the methods by which utilities develop their time-of-use rates. It turns out that proper rate structures incorporate both short-run and long-run marginal costs.

To begin, we assume there are three types of plants. The underlying difference among these plants is the amount of capital used in their construction and the type of fuel. It is also assumed that once on-line, these plants operate at optimal efficiency. We can express capital costs in comparable terms, by dividing the total capital cost of the plant by its capacity in megawatts, and adjusting for the expected number of operating days to measure the capital cost per megawatt per day. For any plant j, we denote this capital cost as C^j.

The short-run marginal cost of operating a power plant is composed mainly of the cost of fuel, compensation of personnel, and maintenance costs. Of these three, the cost of fuel is the most significant. For this reason, the short-run marginal cost is often used synonymously with the term energy cost. For any plant j, the short-run marginal cost to operate it at a capacity of one MW is denoted m^j.

In general, the more capital intensive a plant is, the more efficient it is at converting primary fuels into electrical energy. Thus, for plants x and y with C^x greater than C^y, it is generally true that m^x will be less than m^y.

The three types of plants in our hypothetical model are known as peaker, intermediate and baseload plants. Peaker plants are inexpensive to construct and tend to use a volatile fuel such as natural gas to spin turbines which generate electricity. In contrast, baseload plants are capital intensive, but are very efficient in converting primary fuels into electrical energy. Most nuclear plants are classified as baseload plants. Between these two extremes are the intermediate plants requiring capital costs less than that of the baseload but more than the peaker. An example of an intermediate plant might be a coal-fired station.

Denoting the peaker, intermediate and baseload type plants by P, I, and B, respectively, the capacity costs can be ordered: $C^B > C^I > C^P$, and in general: $m^B < m^I < m^P$. In figure 2.2, we illustrate the daily cost to operate each of these three plants for a given number of hours; loads that last more than h^I hours are most economically produced with the baseload plants. Loads that last between h^P and h^I are produced least expensively by the intermediate-sized plants, while loads lasting less than h^P hours should be generated with peaker plants. Loads of the same size lasting exactly h^P hours of the day can be produced at the same cost using either the peaker

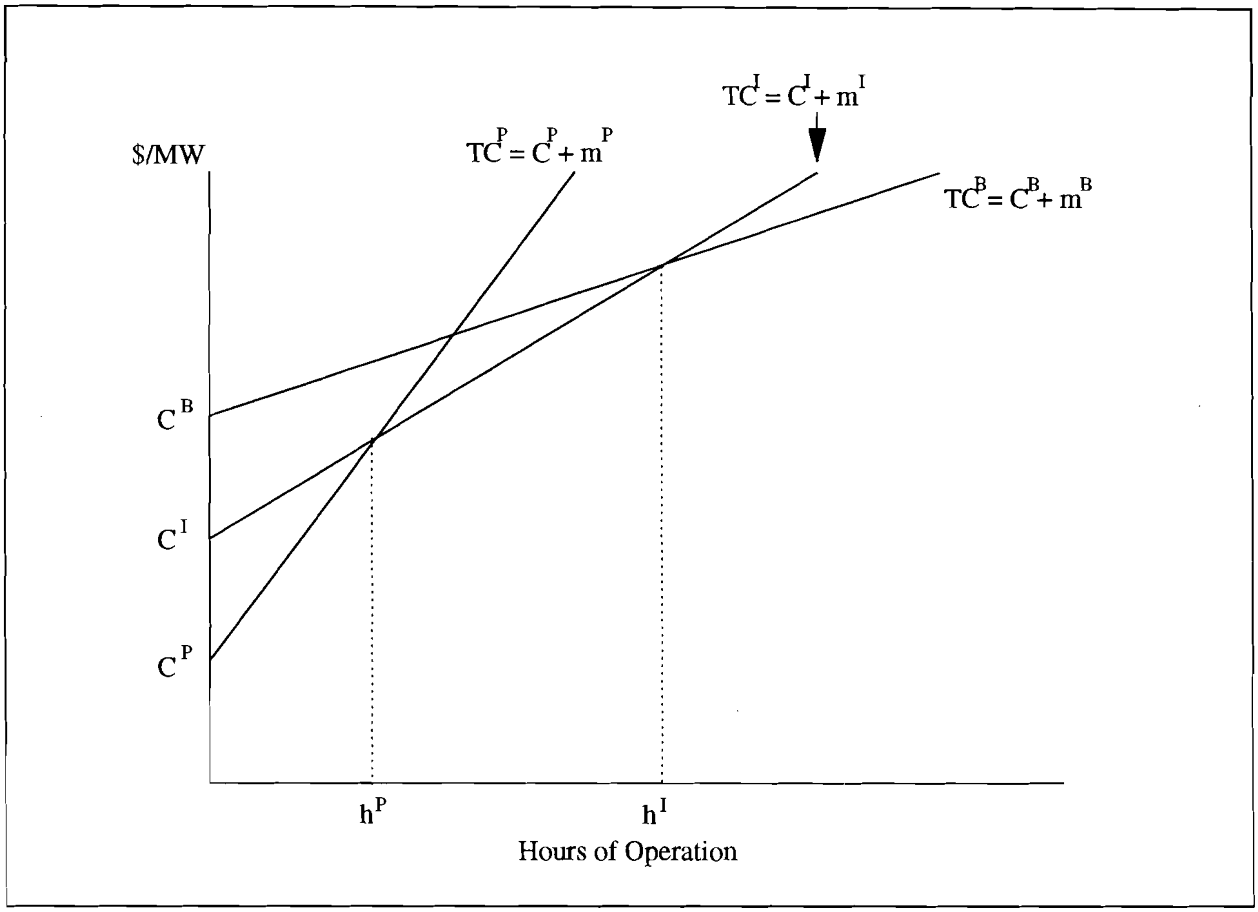

Figure 2.2 Illustrative daily total cost curves for peaker, intermediate, and baseload power plants as a function of hours of operation.

technology or the intermediate technology. That is:

$$C^P + h^P m^P = C^I + h^P m^I$$

This implies that at h^P hours of operation:

$$h^P = \frac{C^P - C^I}{m^I - m^P} \tag{2.1}$$

Similarly, at h^I hours:

$$h^I = \frac{C^I - C^B}{m^B - m^I} \tag{2.2}$$

With the aid of this graph, a "least-cost plan" in which to operate the three different plants can be formulated; it depends on a utility's daily load shape. Figure 2.3 represents hypothetical utility load profile and load duration curves for a typical summer day. The load profile curve gives the system demand corresponding to the different hours of the day. Notice that this system

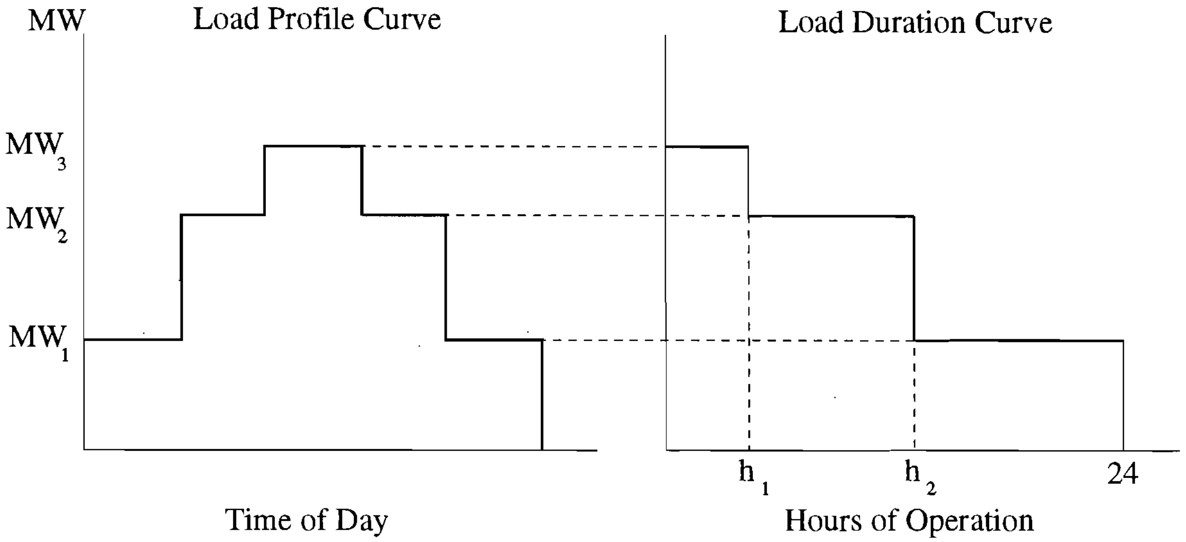

Figure 2.3 Load duration and load profile curves for hypothetical utility.

peaks during the middle hours of the day when air-conditioning is used most intensively The load duration curve gives the number of hours that a specified load exists. For example, loads of MW_3 megawatts last for h_1 hours, loads of MW_2 megawatts for h_2 hours while loads of MW_1 megawatts exist all day.

These latter two figures are combined in figure 2.4. This facilitates the derivation of the least-cost operation schedule summarized in table 2.1. According to this schedule, the baseload technology handles the load of MW_B that runs all day. At time t_1, when demand jumps to MW_I, the intermediate plant comes on line until time t_4 satisfies the additional demand of MW_I - MW_B. Finally, when the system peaks between the hours t_2 and t_3, the peaker plants come on line satisfying the added peak demand of MW_P - MW_I. In this hypothetical example, there are three ways that the utility might be configured at any given time: only the base-load plants in operation (off-peak), both baseload and intermediate plants operating (shoulder), and all three types of plants operating (on-peak). Strict short-run marginal cost pricing would dictate pricing a unit of electricity in each of these three periods according to their marginal costs of production: during

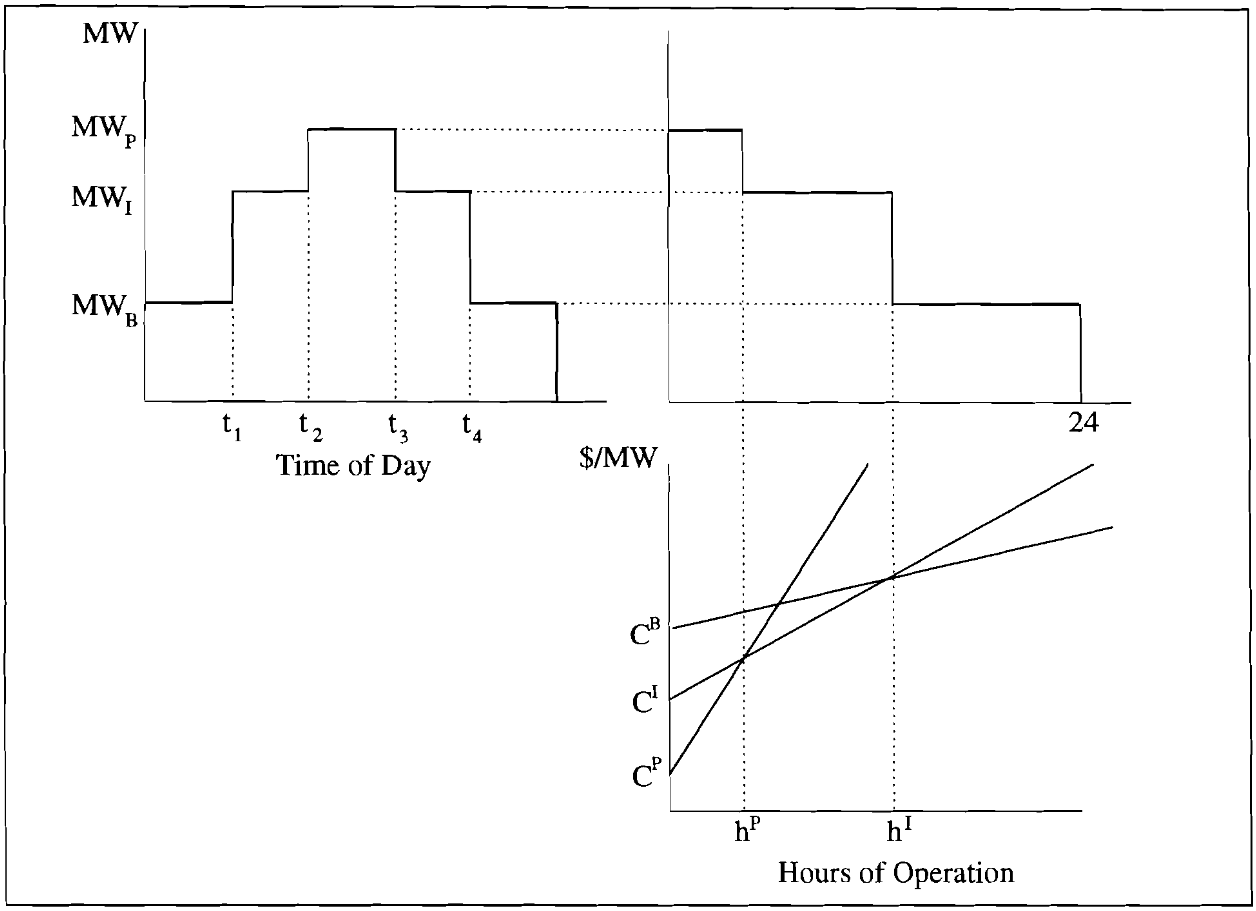

Figure 2.4 Determination of power plant operation schedules from load profile curve, load duration curve, and plant operating cost curves.

Table 2.1 Hours and duration of operation of base, intermediate and peaker power plants.

Plant	Hours of Operation	Duration of Operation
Base	12:00pm - 12:00am	24 hours
Intermediate	t_1 - t_4	h^I - h^P
Peaker	t_2 - t_3	h^P

off-peak hours, charge m^B; during shoulder hours, charge m^I; and during peak hours, charge m^P. When the time arises to expand capacity, the utility and its customers will be burdened with the task of financing a multi-million dollar generating unit. To circumvent this problem, the rates are based on the long-run marginal cost of producing electricity. The long-run marginal cost incorporates the cost of new capacity.

Since it is most often demand during the peak periods that bring about the need for additional capacity, the financing of new generating units should rest primarily on users during this period. Long-run marginal cost pricing then purports that electricity used during the peak periods should be charged the long-run cost of expanding capacity, as well as the energy charges. Electricity consumed during periods other than the peak periods should only be levied the energy charges. Table 2.2 contains the cost that should be levied on users during each of the rating periods.

Table 2.2 Distribution of energy and capacity costs for off-peak, shoulder and peak periods.

	Rating Period		
Charges	Off-peak	Shoulder	Peak
Energy	m^B	m^I	m^P
Capacity	0	0	C^P

To verify this conclusion, we illustrate several case examples that show how system costs and revenues change when demand changes in the different pricing periods.

Case I: Off-Peak Demand Increases by One Megawatt: If we assume that initially the utility is configured in accordance with table 2.2 and the plants operate at full capacity, the total cost of operating the system for one day is:

$$TC_0 = MW_B(C_B + 24m^B) + (MW_I - MW_B)(C^I + h^I m^I) + (MW_P - MW_I)(C^P + h^P m^P).$$

When off-peak demand increases by one unit, it is most efficient to invest in an additional unit of baseload capacity. Increasing baseload capacity by one unit relieves the intermediate plant one unit; therefore, the cost of operating the system is:

$$TC_1 = (MW_B + 1)(C_B + 24m^B) + (MW_I - 1 - MW_B)(C^I + h^I m^I) + (MW_P - MW_I)(C^P + h^P m^P).$$

The change in cost, TC_1 - TC_0, is:

$$\Delta Cost = C^B + 24m^B - C^I - h^I m^I$$

and adding and subtracting $h^I m^B$ gives:

$$\Delta Cost = C^B - C^I + (24 - h^I)m^B + (m^B - m^I)h^I.$$

We know that at h^I hours the total cost of operating a baseload plant is the same as the cost of operating an intermediate plant. Making use of equation (2) and substituting for h^I gives:

$$\begin{aligned}\Delta Cost &= C^B - C^I + (24-h^I)m^B + C^I - C^B \\ &= (24-h^I)m^B.\end{aligned}$$

The change in cost is equal to the energy cost for the additional off-peak electricity consumed and therefore, no capacity costs should be imposed on the off-peak users even if they are solely responsible for the increase in the baseload unit. Schenkel (1993) shows that when only shoulder demand increases by one megawatt, shoulder-period users should pay the energy charge of the intermediate-sized plants.

Case II: Peak Demand Increases One Megawatt: This case is used to show that peak-period users should pay the capacity charge as well as the energy charge. With initial system cost at:

$$TC_0 = MW_B(C_B+24m^B)+(MW_I-MW_B)(C^I+h^Im^I)+(MW_P-MW_I)(C^P+h^Pm^P),$$

the most inexpensive response would be to increase the capacity of the peaker plant one unit. Total system cost would then be:

$$TC_I = MW_B(C_B+24m^B)+(MW_I-MW_B)(C^I+h^Im^I)+(MW_P+1-MW_I)(C^P+h^Pm^P).$$

Therefore, the change in cost TC_1 - TC_0 is:

$$\Delta Cost = C^P + h^Pm^P.$$

This increase in peak demand results in both a capacity charge and an energy charge. It would make sense to charge those users, the peak users, who bring about the need for this expanded capacity the capacity charge of C^P per day in addition to the energy charge.

As a final demonstration of the validity of this rate structure, we consider the case in which demand increases during all hours of the day.

Case III: Demand During All Periods Increases One Megawatt: Obviously the most economical way to satisfy this increased demand would be to expand capacity of the baseload unit. The change in cost is C^B, plus the energy costs, $24m^B$, but we must show that charging rates according to table 2.2 will raise enough revenue to cover this additional cost. The increase in payments from customers is:

$$\begin{aligned}\uparrow Payments &= (24-h^I)m^B+(h^I-h^P)m^I+C^P+h^Pm^P \\ &= 24m^B-h^Im^B+h^Im^I-h^Pm^I+C^P+h^Pm^P \\ &= 24m^B+(m^I-m^B)h^I-h^Pm^I+C^P+h^Pm^P.\end{aligned}$$

Making use of equation (2.2) and substituting for h^I gives:

$$\uparrow\text{Payments} = 24m^B + C^B - C^I - h^P m^I + C^P + m^P h^P$$
$$= 24m^B + C^B - C^I + C^P + (m^P - m^I)h^P.$$

Making use of equation (2.1) and substituting for h^P gives:

$$\uparrow\text{Payments} = 24m^B + C^B - C^I + C^P + C^I - C^P$$
$$= 24m^B + C^B.$$

The increase in payments completely offsets the increase in system costs.

To summarize, in all cases, the increased cost due to expanded demand is offset by the increase in revenues. Rate structures should require that non-peak users pay only the short-run marginal cost while peak users pay the additional capacity costs.

3. CONDITIONAL DEMAND FOR ELECTRICITY BY FARM OPERATIONS AND FARM HOUSEHOLDS

To begin to understand the implications of time-of-use electricity rates on dairy farms throughout New York, it is necessary to estimate the existing demand for electricity on these farms, identifying the differences in demand seasonally, as well as by time of day. This is accomplished in several separate, but related steps, the first of which is to estimate the conditional demands for electricity by farm operation.

We begin by reviewing past studies on the demand for electricity. Emphasis is placed on how the quality of data dictated the development of models and how the eventual collection of "micro" data, which is specific to individual households, allowed for the estimation of conditional demand models. These models make extensive use of non-economic variables such as the stock of appliances, the presence of conservation devices, and demographic characteristics for specific households in explaining electricity demand. An algebraic derivation of conditional demands is then given, followed by a detailed description of the 1988 survey data set used in the analysis. Finally, the estimates for house and farm electricity demand are presented.

Unfortunately, the observations for farms in this data set do not separate farm and household electricity demand. This data set does, however, contain observations on rural households, in addition to customers with farm operations. Observations for rural households are used to estimate conditional demand for residences. By making reasonable assumptions about the existence of markets for all goods, the theory of household production (Singh, Squire, and Strauss, 1986) suggests that farm demand for electricity can be treated separately from that by the household, making it possible to predict farm household demand for electricity and find farm demand as a residual. These residuals are used as dependent variables in estimating the conditional demand for farm electricity.

Review of Past Electricity Demand Studies

Prior to the 1970's most utilities based long-term electrical load forecasts on extrapolation and time trend methods (Berndt, 1991, p. 310). Few relied on econometric methods based on the economics of demand, in which prices and income were important explanatory variables. This reflected the view that, since the demand for electricity was growing steadily over time, prices were a minimal factor affecting the demand for electricity.

Nevertheless, a number of econometric studies modelling the demand for electricity were undertaken. The 1951 model by Houthakker (in Taylor, 1975) is often referred to as the first major study. Houthakker used aggregated data on average electricity consumption, income, marginal prices for electricity and gas, and an electrical appliance stock index to model 42 towns in the United Kingdom. Although the model is relatively simple by today's standards, many present day issues pertaining to the modelling of electricity demand were addressed.

Since the time of Houthakker's pioneering research, academicians have placed more emphasis on econometric issues encountered while modelling electricity demand, especially regarding prices. The problem of prices first evolved out of utilities' use of declining block rate schedules, in which electricity could be purchased in block quantities at successively lower prices. Under this rate structure, the price function is no longer continuous, but rather contains discontinuities at points where the price of electricity changes. It is difficult to find a price to use as an independent variable. Furthermore, simultaneity is introduced because price, often an independent variable, is in turn a function of the dependent variable quantity, and the use of the ordinary least squares estimator leads to upward-biased estimates (Berndt, 1991, p.324). To resolve these problems, Taylor (1975) suggests the use of an "intramarginal" price variable in addition to the customer's true marginal cost. These problems are analyzed in greater detail in the article by Taylor (1975), and in Berndt's (1991) chapter on electricity demand modelling.

Researchers also tried to distinguish between the short-run and long-run demand. The model by Fisher and Kaysen (1962)[6] was one of the first to estimate the short-run demand for electricity. This model postulates that the demand for electricity is a function of customer's

[6]Both the Houthakker model and the Fisher-Kaysen model are also summarized in the article by Taylor (1975).

appliance utilization rates. These utilization rates were in turn functions of the price of electricity, the prices of substitute forms of energy, and income. Like the Houthakker model, Fisher and Kaysen used aggregate data by averaging prices and incomes for households in 47 states. Short-run demand is estimated since the customers' stock of appliances is fixed.

Later models estimated the long-run demand for electricity by allowing variation to occur in the customers' stock of appliances. To model this long-run demand, simultaneous equation approaches were often adopted under the assumption that the stock of appliances is determined endogenously with electricity consumption. Dennerlein (1987), estimates both the long-run demand for electricity and the demand for stock of appliances in a simultaneous approach. In a similar model, Flaig (1990) uses aggregate German household data to estimate the demand for electricity and the demand for household appliances.

While these models worked well for estimating price and income elasticities, rarely were they used to forecast future electricity demand. As noted before, long-term forecasts were most often done with time series and extrapolation methods, methods that furnished utility personnel with fairly reliable forecasts in times of stable economic conditions. As the economic climate experienced by electric utilities changed during the late 1960's, most of the extrapolation methods to forecast future loads became less reliable. Since it can take up to 10 years to construct and bring on-line certain forms of generating capacity, these unreliable forecasts led to power outages and resulted in substantial social costs for both industrial and residential customers (Lurkis, 1982). Consumer's confidence in utilities fell and load forecasting became a prominent issue. It was clear that modifications needed to be made in the methods utilities used to forecast future electricity demand.

To improve forecasts, many utilities began to incorporate appliance-specific estimates of electricity consumption (Parti and Parti, 1980). With this knowledge, utilities could make use of technological progress in appliances in demand forecasting and also implement programs targeted to reduce electricity consumption attributable to certain end uses. One method to estimate the appliance-specific electricity demand is through the use of conditional demand models that use household survey data matched with utility billing data. A more thorough description and algebraic derivation of conditional demand models is now given.

Conditonal Demand Models

Conditional demand models are multivariate regressions that use as independent variables the household stock of appliances, demographic characteristics and other factors that could potentially affect the amount of electricity a customer consumes (EPRI EA-3410, 1984). Like the Fisher and Kaysen model, the demand for electricity is assumed to be a function of utilization rates for household appliances. However, where Fisher and Kaysen assumed that these utilization rates are in turn primarily a function of prices and income, conditional demand models use the additional "micro" data available on the demographic characteristics of each household.

In the terminology of conditional demand models, these "utilization rates" for appliances are referred to as unit energy consumption (UEC) coefficients. Specifically, the UEC coefficient for an appliance is a value or function relating the expected amount of electricity that the appliance will utilize in a given time period.

Conditional demand models have been quite successful at determining UEC coefficients (EPRI EA-3410, 1984). They are also relatively inexpensive since the data are easy to obtain, requiring only billing data and a mailed survey. In contrast, a second method to determine unit energy consumption coefficients entails direct metering of each appliance under study. Although accurate, this method is very costly. A third method rests primarily on the engineering characteristics of the appliance; it does not consider variations in utilization rates across households due to different household characteristics or geographical location of the dwelling (EPRI-EA-3410, 1984; and Parti and Parti, 1980).

Although our objective is not to find UEC coefficients per se, knowledge of them helps in the understanding of the derivation of the conditional demand models that are used in this analysis. To develop an algebraic representation of a conditional demand model assume there are T customers, and denote the electricity use for the t^{th} customer for some specified time period as E_t. Given N appliances, we define d_{it} $(i = 1..N)$ as a dummy variable equal to one when the t^{th} household has the i^{th} appliance and equal to zero otherwise. Denote the UEC coefficient for these specified appliances as U_i $(i=1..N)$. To account for electricity used through unspecified appliances, a UEC coefficient of U_0 is assigned to each household. Thus, the t^{th} household's total energy consumption is:

$$(3.1) \qquad E_t = U_0 + \sum_{i=1}^{N} U_i d_{it}$$

In many cases the U_i's may be functions of customer characteristics affecting how intensively the appliance is utilized. Denoting these customer characteristics by the M element vector **V**, the UEC coefficient for the i^{th} appliance is written as $U_i(\mathbf{V})$ $(i=0..N)$. If the U_i's are linear in these variables, then they may be expressed as:

$$(3.2) \qquad U_i = \sum_{j=0}^{M} b_{ij} V_j \qquad i=0,..,N$$

where V_0 is unity for all households and the b_{ij} are parameters to be estimated. Thus, b_{i0} is the constant term for the i^{th} appliance and b_{ij} is the manner in which the j^{th} household characteristic affects utilization of the i^{th} appliance. Substituting equation (2) into equation (1), and adding an error term e_t assumed to be distributed normally with zero mean and finite variance, the energy consumed for the t^{th} household is:

$$(3.3) \qquad E_t = \sum_{j=0}^{M} b_{0j} V_j + \sum_{i=1}^{N} \sum_{j=0}^{M} b_{ij} V_j d_{it} + e_t$$

Equation (3.3) is linear in its parameters and may be estimated using ordinary least squares. Typically, the dependent variable E_t is obtained from billing data, while the independent variables come from survey data.

Data Used for Estimating Conditional Demands for Farm Households and Dairy Farm Operations

The data used to estimate these conditional demands come from the 1988 Rural Household and Farm Energy Survey conducted by the Departments of Agricultural Economics and Agricultural Engineering at Cornell University. The data were gathered through a mail survey of rural households and farms located throughout upstate New York and served by Niagara Mohawk Power Corporation. Surveys that were returned were matched with billing data supplied by Niagara Mohawk.

Of the 5,816 surveys mailed, 3,858 were returned, a response rate of 66 percent; 1,879 of the survey respondents indicated that they operated farms while the remaining 1,979 did not. Of the 1,879 that operated farms, 1,310 can be classified as dairy farms.

All customers were instructed to complete a section with questions about characteristics of the household that would potentially affect electricity use. Approximately half of the questions required the respondent to circle the appropriate answer (i.e. How do you heat your water?), while the other half required some numerical response (i.e. How many of the following appliances do you have?). Customers indicating they operated dairy farms were instructed to fill out an additional section concerning production levels, milking technology, and configuration of electricity using equipment.

The billing data supplied by Niagara Mohawk spanned approximately 14 months, beginning early 1987. Meters readings took place every other month at approximately 60-day intervals, giving seven readings per customer. Unfortunately, the exact dates at which the meters were read was not known. This knowledge would have enhanced the data by allowing for specific estimates of seasonal variation as other demand studies have incorporated (i.e. Parti and Parti, 1980). Instead, electricity consumption had to be aggregated on a yearly basis by summing the first six billing periods, dividing by the number of days in the six billing periods (to put on a daily basis), and multiplying by the number of days in a year, 365.

The price schedule at the time the survey was conducted and the billing data collected consisted of a customer charge (equivalent to $104.56 per year) and an energy charge of 6.66 cents per Kwh. For this reason, the conditional demand estimates for electricity based on this sample could not include price as an explanatory variable.

For estimating conditional demands, the data set was divided into two subsets: those observations for rural households and those observations for farms. However, in setting up these subsets, a number of restrictions had to be placed on the data in order to remove, for example, unrepresentative outliers and extraneous billing data.

Rural Household Subset

The restrictions on the households are not nearly as extensive as those that also had farms: annual electricity consumption had to be between 3,000 and 25,000 Kwh and the billing days for the first six meter readings could not exceed 370 days but had to be at least 360 days. These restrictions reduced the number of household observations by 335, to a total of 1,644.

Table 3.1 gives descriptive statistics for the 1,644 sample households based on annual electricity consumption in Kwh. As to be expected, dwellings with more occupants and a larger number of rooms use more electricity. Surprisingly, the number of rooms has little affect on electricity consumption; households consuming between 3,000 and 8,000 Kwh annually average just over 7.5 rooms per household, while households consuming over 18,000 Kwhs per year have on average only one more additional room. Perhaps the major reason for why the number of rooms in the house does little to affect electricity use is that only a small proportion of customers in this sample use electricity as a primary heat source. The proportion of customers with secondary electric heat, electric water heaters, dishwashers and air conditioners suggests that these appliances are considerably more important in determining the customer's electricity use.

Table 3.1 Characteristics of households from 1988 survey data set.

	Total annual Kwh			
	3,000 to 8,000	8,001 to 13,000	13,001 to 18,000	over 18,000
N	571	611	338	124
Avg. number of people	2.4	3.07	3.96	3.88
Avg. number of rooms	7.53	7.96	8.32	8.56
Percent with primary electric heat	1%	1%	3%	6%
Percent with secondary electric heat	11%	19%	19%	25%
Percent with electric water heater	52%	68%	80%	84%
Percent with dishwasher	21%	40%	47%	55%
Percent with air conditioning	5%	10%	11%	19%
Avg. number of refrigerators	1.19	1.24	1.31	1.40

Source: 1988 Rural Household and Farm Energy Survey.

The conditional demand equations below examine these characteristics in a more systematic fashion.

Farm Subset

In contrast, it was much more difficult to derive a usable sample for the respondents with dairy farms since many failed to provide complete data needed for the analysis and some of the responses made little sense. Consequently, a number of restrictions were placed on the farms to derive a usable sample. Table 3.2 lists criteria, along with the frequency of not passing the criteria, that each farm had to pass in order to be included in the sample. After all of these criteria are taken into account, 275 farms remained.

In looking at table 3.2 milk production per cow, total Kwh/year and number of billing accounts are the most restrictive criteria, with only 73.9, 71.3 and 37.1 percent of the farms

Table 3.2 Screening criteria for dairy farms.

Criteria	Critical Value	Cases Passing	Percent of 1,310
Milk per cow	Between 5,000 and 25,000 lbs annually	968	73.9
Months in production	Milk at least 10 months out of year	1,194	91.1
Average price paid per Kwh	$.06-$10	1,272	97.1
Total Kwh/year*	Between 30,000 and 125,000 Kwh	934	71.3
Number of billing days for six meter readings	300 or more	1,302	99.4
Number of cows	20 or more	1,229	93.8
Acres of land farmed	20 or more	1,275	97.3
Milking system	Parlor, Pipeline or Buckets	1,156	88.2
Annual Kwh per cow	200 or more	1,159	88.5
Annual production of milk in pounds	More than 0	1,038	79.2
Number of billing accounts	One	486	37.1
All combinations		275	21.0

Source: 1988 Rural Household and Farm Energy Survey.
*Includes House

passing, respectively. The milk per cow criterion was imposed to eliminate so called "hobby" farmers and to remove responses that were likely filled out in error with respect to milk production. Farmers that have a large number of cows but produce very little milk are removed by restricting average production per cow to be at least 5,000 pounds per year. Likewise, by restricting average production to be less than 25,000 pounds per cow removes possible errant responses caused by over-stating milk production in the survey.

The justification for the accounts criterion is also worth noting. Customers operating farms were asked in the survey to indicate how many different electricity billing accounts they had with Niagara Mohawk. Of the 1,310 dairy farm responses, about half indicated that they had more than one account. These multiple billing accounts pose a problem since it isn't exactly known how many accounts are included in the Niagara Mohawk billing data. Consequently, the customers actual electricity consumption could be under-represented in the event that some of the billing accounts are not included in the billing data. To circumvent this problem, it was decided to use only those farms that indicated that they had one account.

Table 3.3 contains data for the 275 sample dairy farms. The data suggest that herd size and milk production are important in determining the quantity of electricity consumed. There also exists noticeable trends with respect to the proportion of farms using different milking technology; farms using considerably more electricity tend to use parlor and pipeline technologies, while farms using comparably less electricity tend to use a bucket milking system.

Table 3.3 Characteristics of dairy farms from 1988 survey data set.

	Herd Size			
	50 and under	51 - 75	76-100	Over 100
N	71	103	53	48
Avg. herd size	42	64	88	136
Annual CWT production	5,807	9,530	13,327	20,356
Avg. pounds/cow	13,609	14,996	15,065	14,905
Milking Technology				
Bucket	28 (39.4%)	14 (13.6%)	1 (1.9%)	2 (4.2%)
Pipeline	42 (59.2%)	80 (77.7%)	35 (66.0%)	17 (35.4%)
Parlor	1 (1.4%)	9 (8.7%)	17 (32.1%)	29 (60.4%)
Percent with electric water heater	96%	94%	87%	80%
Percent with heat transfer system	15%	38%	58%	67%
Percent with precooler	1%	13%	15%	31%
Avg. number of milking units	5	5	6	9

Source: 1988 Rural Household and Farm Energy Survey.

A final note to be made about the 1988 data set concerns milk precoolers. In general, there are two kinds of precoolers: ones that make ice used to chill milk prior to entering the bulk tank cooler, often called icebanks, and others that, instead of ice, use well water which is pumped from the ground. While both systems reduce bulk milk cooler electricity consumption, they both also use electricity through the utilization of compressors and water pumps. Consequently, the net electrical input for milk cooling purposes on a farm may differ depending on what type of system is used. In the survey, customers were asked to indicate whether or not their farm used a milk precooler with no regard to the type of milk cooler.

Estimating the Rural Residential Demand for Electricity

Based on equation (3.3), the empirical estimates for the conditional demand for electricity by rural households are presented in this section. Initially, a number of models were estimated that followed closely the format of the conditional demand model derived above; dummy variables for major appliances were interacted with characteristics of the household believed to affect the appliances' use. By including certain socio-economic variables without appliance interaction, the statistical results improved, both in terms of overall explanatory power and the signs on the coefficients. Since the primary goal is to estimate the total demand for electricity by the household, this latter model is used in subsequent analysis. Although this results in some loss of appliance-specific explanatory power, this loss is justified through the increased improvement in overall fit. Tables 3.4 and 3.5 define the variables used in the regressions.

Table 3.6 contains the estimated rural household demand for electricity. The dependent variable in this regression is the household's average daily Kwh, obtained by dividing the household's annual electricity consumption, based on the first six billing periods, by the number of days in the year, 365.[7] In the models, virtually all of the estimated coefficients have the expected signs. Many of the t-ratios are above two, indicating that they are significant in explaining household electricity consumption. Where this is not true, the variable was retained for theoretical consistency and to improve the predictive power.

Based on the regression results, each room in the dwelling increases daily electricity consumption by about one half of a Kwh. Not surprisingly, electricity consumption is correlated positively with the number of people (PEOP). Households that close rooms off in the winter

[7] The number of observations used in the regression, 1,540, is less than the number of observations obtained after cleaning the data, 1,644, due to missing responses to some of the survey questions.

Table 3.4 Variable definitions for household appliances.

Variable	Definition	Variable	Definition
PSH	Dummy for primary electric heating	PUMP	Dummy for well water pump
SSH	Dummy for secondary electric heating	DEHUM	Dummy for dehumidifier
H2O	Dummy for electric water heating	POOL	Dummy for swimming pool pump
CW	Dummy for clothes washer	CLRTV	Number of color TVs
ELECRGE	Dummy for electric cooking range	BWTV	Number of black and white TVs
FF	Number of frost free refrigerators	VCR	Dummy for VCR
MD	Number of manual defrost refrigerators	PC	Dummy for personal computer
MICRO	Dummy for microwave	ACOND	Dummy for air conditioning
DW	Dummy for dishwasher	H2OBED	Dummy for water bed
CD	Dummy for electric clothes dryer	HOTTUB	Dummy for hot tub
FIRE	Dummy for fire place		

realize significant savings, as reflected by the signs and magnitudes of the CLOSE and CLSRMS variables.

Customers that own their home tend to use less electricity than those who rent. One possible explanation is that owners may be more willing to invest in conservation devices and are more conscientious of their electrical expenses than renters, particularly if utilities are included in the rent. Clock thermostats, which can be set manually by the owner and allow heating to be turned off when no occupants are in the home, are efficient, saving about 476 Kwh per year (365days*1.305Kwh/day).

The negative signs for full time and part time workers, FULL and PART, respectively, seem to make sense; the more working occupants, the less electricity consumed since fewer occupants are around during the day.

It is apparent from the signs and magnitudes of AGEHOMEA and AGEHOMEB that homes built within four years of 1988 are considerably more energy efficient than older homes. However, there seems to be no good explanation why the coefficient on AGEHOMEC,

Table 3.5 Variable definitions for household demographic characteristics.

Variable	Definition	Variable	Definition
OTHBUI	Dummy if not standard or mobile home	FULL	Number of full time workers
ROOMS	Number of rooms	PART	Number of part time workers
CLOSE	Dummy for closing rooms off in the winter	GAS	Dummy for gas primary heat
CLSRMS	Number of rooms closed of in winter	WOOD	Dummy for wood primary heat
OWN	Dummy if home is owned	FLOW	Number of faucet flow restrictors
CLOCK	Dummy for clock thermostat	BLANKET	Dummy for hot water blanket
OTHER	Dummy for any other conservation devices	SQRPEOP	Number of people squared
PEOP	Number of people	INCOMEA	Less than $5,000
AGEA	# Occupants under 2	INCOMEB	$5,000 to $9,999
AGEB	# Occupants 2 to 5	INCOMEC	$10,000 to $12,499
AGEC	# Occupants 6 to 12	INCOMED	$12,500 to $14,999
AGED	# Occupants 13 to 17	INCOMEE	$15,000 to $19,999
AGEE	# Occupants 18 to 34	INCOMEF	$20,000 to $24,999
AGEF	# Occupants 35 to 61	INCOMEG	$25,000 to $34,999
AGEG	# Occupants 62 to 64	INCOMEH	$35,000 to $49,999
AGEH	# Occupants over 65	INCOMEI	$50,000 to $74,999
EDUCA	Elementary school highest education of household head	INCOMEJ	$75,000 or more*
EDUCB	Some high school highest education of household head	AGEHOMEA	Less than 2 years
EDUCC	High school graduate highest education of household head	AGEHOMEB	2 to 4 years
EDUCD	Some college highest education of household head	AGEHOMEC	5 to 7 years
EDUCE	College graduate highest education of household head	AGEHOMED	8 to 20 years
EDUCF	Post graduate highest education of household head*	AGEHOMEE	21 to 40 years
		AGEHOMEF	Over 40 years*

* - Indicates variable not included in regression but incorporated in intercept term.

representing homes between the age of five to seven years, is so large and positive when the trend in the other variables suggests that it should be negative.

The coefficients on the two electric heat variables, SSH and PSH, work quite well in explaining electricity consumption as noted by their high t-ratios, 4.1 and 5.2, respectively. A

Table 3.6 House regression results.

Parameter	Estimate	t-ratio	Parameter	Estimate	t-ratio
INTERCEP	8.289	3.552	INCOMEG	-1.255	-1.219
OTHBUI	2.077	1.61	INCOMEH	-0.539	-0.508
ROOMS	0.58	4.194	INCOMEI	0.357	0.289
CLOSE	-1.277	-1.432	AGEHOMEA	-15.22	-3.329
CLSRMS	-0.439	-1.49	AGEHOMEB	-13.448	-2.672
OWN	-0.551	-0.593	AGEHOMEC	7.684	1.773
CLOCK	-1.305	-1.365	AGEHOMED	-2.262	-1.749
OTHER	-1.778	-1.279	AGEHOMEE	0.297	0.282
PEOP	1.165	1.297	GAS	-0.209	-0.263
AGEA	0.974	0.742	WOOD	1.036	1.608
AGEB	-0.5	-0.481	SSH	2.814	4.059
AGEC	-0.481	-0.517	PSH	10.402	5.226
AGED	1.924	2	H2O	-3.9	-2.199
AGEE	0.581	0.642	H2O*PEOP	3.739	5.712
AGEF	1.927	2.175	H2O*SQRPEOP	-0.384	-5.608
AGEG	1.216	1.152	H2O*CW	4.171	3.597
AGEH	-0.474	-0.511	H2O*BLANKET	-0.911	-1.115
FULL	-0.709	-1.53	H2O*FLOW	-0.331	-0.597
PART	-0.184	-0.396	ELECRGE	2.228	3.736
EDUCA	-2.856	-1.877	FF	2.52	3.962
EDUCB	-0.368	-0.319	MD	1.057	1.886
EDUCC	0.291	0.292	MICRO	0.573	0.902
EDUCD	-0.985	-0.968	BWTV	-0.523	-1.301
EDUCE	-0.426	-0.399	CLRTV	-0.326	-0.85
INCOMEA	2.724	1.654	VCR	0.377	0.708
INCOMEB	-1.457	-1.185	PC	-0.626	-0.896
INCOMEC	0.085	0.063	ACOND	1.397	2.393
INCOMED	-1.254	-0.9	H2OBED	1.923	3.171
INCOMEE	-0.415	-0.344	FIRE	-0.533	-1.378
INCOMEF	-0.265	-0.234	HOTTUB	2.278	1.184
	N = 1540			$R^2 = 0.44$	

coefficient value of 10.4 on PSH indicates that primary space heating increases annual electricity consumption by just under 4,000 Kwhs.

Of all the appliances, only the water heater is modeled in true conditional demand format according to equation (3.2), in which it is interacted with socio-economic variables. In this analysis, the equation to determine the UEC is specified as:

$$UEC_{H2O} = -3.9 + 3.7*PEOP - 0.84*SQRPEOP + 4.2*CW - 0.91*BLANKET - 0.33*FLOW.$$

The negative sign on the people "squared" coefficient suggests that there are economies of size with respect to electricity use for water heating. The results of this UEC equation also suggest that the use of a blanket for the water heater and low flow restrictors cut down daily electricity consumption by about 0.9 and 0.3 Kwh, respectively, for those homes with electric water heaters.

The signs and magnitudes of the coefficients corresponding to the household's income, age of its occupants, and educational attainment level of the household head are somewhat difficult to interpret. Furthermore, many of the coefficients are not significant but were included only to increase the explanatory power of the model.

The remaining variables are either dummy or continuous variables for other relevant appliances. Most of the coefficients for these variables have the correct sign, with the exception that there seems to be no clear justification for the negative signs on the television variables, BWTC and CLRTV. The negative sign on the dummy for a PC computer suggests that households that have a PC might be better organized than those that don't, and thus, might be more conscious of their electrical consumption.

Estimating the Farm Demand for Electricity

After "forecasting" farm household electricity demand by substituting the farm household characteristics into the demand equation from table 3.6, an estimate of farm electricity use can be obtained by subtracting household consumption from total consumption. Using these estimated farm electricity consumption figures as dependent variables, it is possible to estimate the demand for electricity on the farm.

As for households, farm electricity demand is assumed to be a function of farm characteristics and the stock of electrical machinery, i.e. a conditional demand. Table 3.7 defines these characteristics and machinery variables used in the farm electricity demand regression and Table 3.8 contains the farm regression results.[8]

This model seems to have performed well. The overall fit, as measured by the $R^2 = 0.7$, is quite good for this type of cross-sectional data. The sign of the SQRMILK term indicates that there are economies of size in dairying with respect to electricity use. The magnitude of the coefficient on heat transfer variable, -6.3, indicates that this device is a significant conservation measure. Also, bucket milking systems use considerably less electricity than pipeline and parlors.

Table 3.7 Variable definitions for dairy farms.

Variable	Definition
FANS	Number of fans
ELECH2O	Electric water heater
HT	Heat transfer system
PRECOOLER	Milk precooler
MILK	Milk production in thousands of pounds
SQRMILK	Square of milk production
LIGHTS	High efficiency lighting
BUCKET	Bucket milking system
PIPELINE*	Pipeline milking system
PARLOR	Parlor milking system
UNITS	Number of milking units
SQRUNITS	Square of number of milking units

* - Omitted from regression and incorporated in intercept term.

[8]Again, because of omitted responses, the number of observations included in the regression, 268 is slightly less than the number of sample farms, 275.

Table 3.8 Farm regression results.

Parameter	Estimate	Standard Error	t-ratio
INTERCEP	0.641	12.642	0.051
FANS	5.111	0.901	5.671
ELECH2O	29.189	7.723	3.779
HT	-6.338	4.898	-1.294
PRECOOLER	3.590	6.470	0.555
LIGHT	-0.568	4.879	-0.116
MILK	0.091	0.013	6.965
SQRMILK	$-1.01*10^{-5}$	$3.5*10^{-6}$	-2.879
BUCKET	-20.188	6.622	-3.049
PARLOR	16.236	6.428	2.526
UNITS	1.841	1.364	1.350
SQRUNIT	-0.041	0.021	-1.939
	N = 268	R^2 = .6844	

4. TIME-OF-DAY ELECTRICITY DEMAND ON DAIRY FARMS

These yearly conditional demand relationships for electricity by the dairy farm business are only part of the information needed to study the effects of time-of-use rates on dairy farming. We must also know the electricity demand by time of day. We begin the discussion by briefly describing past studies dealing with this issue. Some of these studies used the cubic spline regression model, but the majority focused on residential power use. Following this introduction, we derive the cubic spline regression model and demonstrate how it can be used to model electricity demand by time of day for dairy farms. A brief description of the data used in the analysis is followed by a discussion of the empirical results.

Early Time-of-Day Demand Studies

Until about 20 years ago, interest in electricity demand modelling focused mainly on estimating the total demand in a given accounting period, such as a month or a year. Since most utilities used flat or declining block rates, little emphasis was placed on the distribution of this electricity by time of day. Concern for rising energy prices and the increased focus on the need for energy conservation in the early 1970's prompted the Federal Energy Administration (later the Department of Energy) in the mid 1970's, to sponsor 14 residential pricing experiments on the effectiveness of time differentiated rates (Caves, 1984). Hourly electricity consumption data were gathered for large numbers of residential customers from all regions of the country. Some of these pricing experiments concluded that TOU rates were an effective method in inducing customers to shift peak demand. As a result, Congress included in the 1978 Public Utility Regulatory Policies Act (PURPA) a provision compelling state regulatory commissions nationwide to study the feasibility of implementing time-of-use rates (Munasinghe, 1990, p.126). Since that time, numerous studies modelling electricity demand by time of day and customer's response to TOU pricing have been undertaken.

One common approach to these studies was to aggregate daily electricity consumption into a small group of distinct intervals. These intervals may correspond to the specific hours of the day (1 to 24), to the different periods (i.e. peak, shoulder and off-peak), or to different seasons. After aggregation, consumption of electricity in each interval is treated as a separate good, each with its own price and contribution to consumer utility. In 1971, Cargill and Meyer were among the first to use this strategy to estimate the total system demand for each hour of the day for two different regions, although their model does not distinguish the demand by customer class (i.e. residential, commercial, or industrial).

Hausman *et al.* (1979, in EPRI report EA-1304) develops a two-level budgeting model where customers first allocate a share of their income to electricity, and then decide how to distribute this electricity throughout the day under time-of-use pricing. They apply this theory to Connecticut residential household data. In cases where time periods of interest do not correspond to the hours of the day, such as the Hausman analysis in which nighttime hours are aggregated, the estimated functions do not generate the necessary information to predict a load curve. Rather, they yield estimates for consumption of electricity in each period. These models are often employed to estimate the customer's response to TOU rates by deriving own and cross price elasticities of demand for periods of interest.[9]

The second common approach to modelling time-of-day electricity demand proceeds in two stages, both of which involve some sort of regression or estimating routine. In the first stage, a time-series regression is used to parameterize each customer's load curve by a fixed number of coefficients. Then, in the second stage, these coefficients are used as dependent variables in a regression to explain how they differ across households. Granger *et al.* (1979) applies a two-stage method to analyze time-of-day electricity demand for 400 Connecticut residents. In the first stage, a matrix of hour dummy variables and a number of other variables to explain day-to-day variation in the load shape for a given customer are regressed on hourly electricity use levels. The second stage entails regressing demographic characteristics of the 400 households on these first-stage coefficients.

Another widely used two-stage model, which is the basis for the model developed here, uses the concept of a cubic spline (Hendricks *et al.*, 1979). Leaving details to later, the first stage consists of parameterizing each customer's load curve as a select number of coefficients that serve as the ordinate values to be fitted with a cubic spline. The second stage uses these estimated coefficients as dependent variables in a regression to explain how they vary across households. The independent variables in this second stage are household appliance stock, demographic characteristics, and other relevant factors that determine the level of electricity demand at a particular moment. The advantage of this type of two stage model, in contrast to the type employed by Granger, is the considerably smaller number of second-stage regressions and hence relevant parameters involved.

The 1979 model of Hendricks *et al.* serves as an example. This analysis uses residential time-of-day consumption data for 400 Connecticut households to study the effectiveness of time-of-day rates in inducing customers to shift peak loads to off-peak periods. Although the model did not work very well in achieving its primary goal (i.e. determining the effectiveness of TOU pricing), the empirical results suggest that the cubic spline regression model is useful for estimating the impact of demographic characteristics on the shape of the load curve for residential customers.

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[9]Other articles may be found in the EPRI report EA-1304 entitled *Modeling and Analysis of Electricity Demand by Time-of-Day* and the 1984 *Journal of Econometrics* Annals issue entitled *The Welfare Econometrics of Peak-load Pricing for Electricity*.

Another example is the earlier model by Hendricks *et al.* (1977). This model differs from Hendricks' and Koenker's (1980) later work in that the first- and second-stage regressions are incorporated into a single regression. The purpose of the analysis was to illustrate a model to determine the consumption pattern exhibited by a household. No price variables were incorporated since the customers were not subjected to time-of-day rates. The purpose of the analysis was to explain the consumption pattern for different households.

Cubic Spline Regression Model[10]

This type of regression model hinges on the concept of a cubic spline. A cubic spline can be defined as a series of polynomial functions (of at most degree three) joining one another at points known as knots. There are also two knots corresponding to the extremes. Together these polynomial functions represent one continuous piecewise function. In the case of electricity modelling, this function represents the load curve.

Evaluating any two adjacent polynomials at their common knot yields the same ordinate value, as well as equal first and second derivatives. The third derivative is a step function with discontinuities occurring at the knots. A cubic spline is said to be periodic if the ordinate value, first derivative, and second derivative evaluated at the two extreme knots are equal, respectively. The periodic cubic spline is employed since electricity consumption on a dairy farm does exhibit a daily periodic nature.

Mathematically, the periodic cubic spline, S(x) for $x_0 \leq x \leq x_k$, with knot locations at $\{x_o, x_1, x_2, \ldots, x_k\}$ and associated ordinate values $\{y_o, y_1, y_2, \ldots, y_k\}$, where $y_o = y_k$, can be defined as a series of k polynomials with degree at most three satisfying the following requirements:

$$S(x) = \begin{cases} S_1(x) & x_0 \leq x \leq x_1 \\ S_2(x) & x_1 \leq x \leq x_2 \\ \vdots & \\ \vdots & \\ S_k(x) & x_{k-1} \leq x \leq x_k \end{cases}$$

$$S_j(x_j) = y_j = S_{j+1}(x_j) \text{ for } j=1,2..k-1$$
$$S_k(x_k) = y_k = S_1(x_0)$$

[10]Much of the notation is taken from Poirier (1976).

$$S_j'(x_j)=S_{j+1}'(x_j) \text{ for } j=1,2..k-1$$
$$S_k'(x_k)=S_1'(x_0)$$

$$S_j''(x_j)=S_{j+1}''(x_j) \text{ for } j=1,2..k-1$$
$$S_k''(x_k)=S_1''(x_0).$$

These requirements imply the following continuity conditions[11]:

$$(1-\lambda_j)M_{j-1}+2M_j+\lambda_j M_{j+1}= \frac{6y_{j-1}}{h_j(h_j+h_{j+1})}-\frac{6y_j}{h_j h_{j+1}}+\frac{6y_{j+1}}{h_{j+1}(h_j+h_{j+1})}$$

for j = 2,....,k-1 and

$$(1-\lambda_k)M_{k-1}+2M_k+\lambda_k M_1= \frac{6y_{k-1}}{h_k(h_k+h_1)}-\frac{6y_k}{h_k h_1}+\frac{6y_1}{h_1(h_k+h_1)}$$

$$(1-\lambda_1)M_k+2M_1+\lambda_1 M_2= \frac{6y_k}{h_1(h_1+h_2)}-\frac{6y_1}{h_1 h_2}+\frac{6y_2}{h_2(h_1+h_2)}$$

where:

$$M_j=S''(x_j) \quad (j=0,1,2...k)$$
$$h_j=x_j-x_{j-1}$$
$$\lambda_j=\frac{h_{j+1}}{h_j+h_{j+1}} \quad (j=1,2,3...k-1)$$
$$\lambda_k = \frac{h_1}{h_k+h_1}.$$

This results in a system of k equations in k unknowns, the unknowns being the M_1, M_2....M_k. To determine the values of these unknowns, define the two (k x k) matrices:

[11]The derivation of these continuity conditions may be found in appendix I.

$$\Lambda=\begin{bmatrix} 2 & \lambda_1 & 0 & \cdots & 0 & 0 & 1-\lambda_1 \\ 1-\lambda_2 & 2 & \lambda_2 & \cdots & 0 & 0 & 0 \\ 0 & 1-\lambda_3 & 2 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 2 & \lambda_k & 0 \\ 0 & 0 & 0 & \cdots & 1-\lambda_{k-1} & 2 & \lambda_{k-1} \\ \lambda_k & 0 & 0 & \cdots & o & 1-\lambda_k & 2 \end{bmatrix};$$

and

$$\Theta=\begin{bmatrix} -\frac{6}{h_1h_2} & \frac{6}{h_2(h_1+h_2)} & 0 & \cdots & 0 & 0 & \frac{6}{h_1(h_1+h_2)} \\ \frac{6}{h_2(h_2+h_3)} & -\frac{6}{h_2h_3} & \frac{6}{h_3(h_2+h_3)} & \cdots & 0 & 0 & 0 \\ 0 & \frac{6}{h_3(h_3+h_4)} & -\frac{6}{h_3h_4} & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -\frac{6}{h_{k-2}h_{k-1}} & \frac{6}{h_{k-1}(h_{k-2}h_{k-1})} & 0 \\ 0 & 0 & 0 & \cdots & \frac{6}{h_{k-1}(h_{k-1}+h_k)} & -\frac{6}{h_{k-1}h_k} & \frac{6}{h_k(h_{k-1}+h_k)} \\ \frac{6}{h_1(h_k+h_1)} & 0 & 0 & \cdots & 0 & \frac{6}{h_k(h_k+h_1)} & -\frac{6}{h_kh_1} \end{bmatrix}$$

and the vectors

$$M = [M_1, M_2, \ldots, M_K]'; \text{ and } \quad y = [y_1, y_2, \ldots, y_k]'.$$

The continuity conditions can be written in matrix notation as:

$$\Lambda M = \Theta y.$$

Since it is a system of k equations in k unknowns, it can be solved:

$$M = \Lambda^{-1}\Theta y.$$

A method for obtaining the coefficients for the individual polynomials is derived in appendix II. Alternatively, through the use of matrices, it is possible to construct any n dimensional vector $\eta = S(\xi)$ of cubic spline interpolants for a given vector $\xi = [\xi_1, \xi_2, \xi_3, \ldots, \xi_n]$ of abscissa values, where $\xi_1 \geq x_0$ and $\xi_n \leq x_k$. (In the case of electricity demand modelling, the vector ξ corresponds to the hours of the day: $\xi = [1,2,3...24]$). To do this, define the two n x k matrices P and Q such that for $x_{j-1} \leq \xi_i \leq x_j$, (i = 1,2,3...n) (j=2,3,....,k):

$$p_{im} = \begin{cases} (x_j-\xi_i)[(x_j-\xi_i)^2-h_j^2]/6h_j, & \text{for } m=j-1 \\ (\xi_i-x_{j-1})[(\xi_i-x_{j-1})^2-h_j^2]/6h_j, & \text{for } m=j \\ 0, & \text{otherwise} \end{cases}$$

$$q_{im} = \begin{cases} \dfrac{(x_j-\xi_i)}{h_j}, & \text{for } m=j \\ \dfrac{(\xi_i-x_{j-1})}{h_j}, & \text{for } m=1 \\ 0, & \text{otherwise} \end{cases}$$

and for j=1:

$$p_{im} = \begin{cases} (x_1-\xi_i)[(x_1-\xi_i)^2-h_1^2]/6h_1, & \text{for } m=k \\ (\xi_i-x_0)[(\xi_i-x_0)^2-h_1^2]/6h_1, & \text{for } m=1 \\ 0, & \text{otherwise} \end{cases}$$

$$q_{im} = \begin{cases} \dfrac{(x_j-\xi_i)}{h_j}, & \text{for } m=j \\ \dfrac{(\xi_i-x_{j-1})}{h_j}, & \text{for } m=1 \\ 0, & \text{otherwise} \end{cases}.$$

Using the representation of S(x) in terms of **M** derived in appendix III:

$$S(x) = \frac{(x_j-x)}{6h_j}\left[(x_j-x)^2-h_j^2\right]M_{j-1} + \frac{(x-x_{j-1})}{6h_j}\left[(x-x_{j-1})^2-h_j^2\right]M_j + \frac{(x_j-x)y_{j-1}}{h_j} + \frac{(x-x_{j-1})y_j}{h_j},$$

and it is clear that the vector of ordinate values can be written:

$$\begin{aligned} S(\xi) &= PM+Qy \\ &= (P\Lambda^{-1}\Theta+Q)y. \quad \text{Since } M=\Lambda^{-1}\theta y \\ &= Wy \end{aligned}$$

where the n x k matrix W is defined as:[12]

$$W=P\Lambda^{-1}\Theta+Q.$$

At this point we can already get an appreciation for how cubic splines can be used to model electricity demand. The first step is to compose a vector of knot locations and for each knot, regress the farm characteristics on the observed ordinate values from the billing data. This yields the vector y estimates that relate how farm characteristics determine the level of electrical demand at the knots. Then, the cubic spline interpolants are found by multiplying y by the appropriate W matrix and a load curve is formed.

An additional step, the first regression, that leads to better results, incorporates all 24 hours of the data by using estimated ordinate values at the knots which minimize the squared deviations between the cubic spline and the true load curve. In other words, we use ordinate values that give the best fitting cubic spline rather than the actual values. This procedure works because a cubic spline always goes through the ordinate values corresponding to the knots.

To develop this first-stage regression, we define $\xi = [1,2,..,24]'$ as the vector of abscissa values corresponding to the hours of the day. Associated with ξ are the observed ordinate values from the billing data denoted by:

$$\eta[\eta_1,\eta_2,...,\eta_{24}]' = S(\xi)+\varepsilon$$

where $\varepsilon = [\varepsilon_1, \varepsilon_2,...,\varepsilon_{24}]'$ is a vector of independent normally distributed error terms such that $E(\varepsilon) = 0$ and $E(\varepsilon\varepsilon') = \sigma^2 I_{24}$, where σ^2 is the variance of η. If we assume that $S(\xi)$ can be represented by a cubic spline, then:

$$\eta = Wy+\varepsilon$$

since $S(\xi) = Wy$.

By replacing the vector y with the parameter vector β, we have:

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[12]A SAS program to construct the W matrix is found in Schenkel, 1993.

$$\eta = W\beta + e$$

where e is a vector of observed disturbance terms. β may now be estimated by ordinary least squares:

$$b = (W'W)^{-1}W'\eta.$$

This first-stage regression estimates the ordinate values at the knots which minimize the sum of squared error between the cubic spline and the actual observed values from the billing data. Therefore, the use of the vector b instead of y leads to a more precise load curve. Figure 4.1 illustrates the improvement of using the least squares cubic spline, denoted CSRM, as opposed to the cubic spline for a 55 cow dairy farm with knot vector x = [5,8,11,12,17,24].[13] At the knot values the cubic spline and actual values are equal as indicated by the markers.

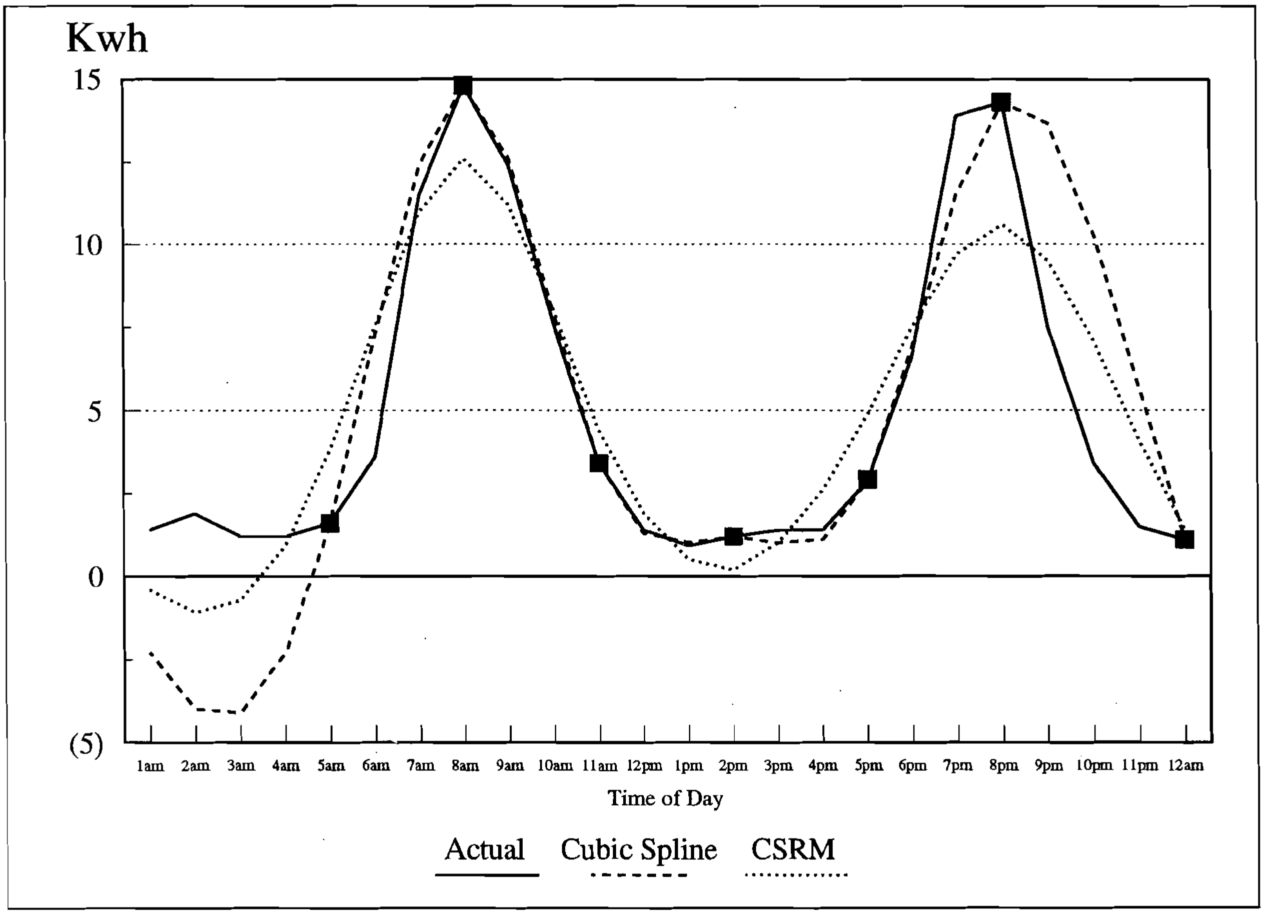

Figure 4.1 Actual, cubic spline, and cubic spline regression model load curves.

[13]This is the vector associated with knots located at 5am, 8am, 11am, 2pm, 5pm, 8pm and 12am.

This first-stage regression must be carried out for each load curve. Instead of doing them all individually, the model can be stacked and the estimates obtained in a single step. To do this, construct the matrix $\mathbf{A}_{Tx24}$ of observed data, where T is the number of load curves for which the first-stage regression must be done. Then $\mathbf{B}_{kxT}$, the matrix of estimators is:

$$B = (W'W)^{-1}W'A.$$

The second stage of the model is to estimate parameters that determine β, the matrix of first-stage cubic spline estimates. Assuming these are linear functions of the farm characteristics, OLS can be applied.

Data Used for Estimating Time-of-Day Electricity Demand

Ideally, a study of this kind should be based on hourly load data for the same sample of farms used to separate farm household electricity consumption from that used on the farm. Unfortunately, these load data do not exist. As an alternative, data on hourly electricity demand for 26 dairy farms located throughout the state of Wisconsin and parts of Minnesota are used.

Furnished by Dairyland Power Corporation of Wisconsin, electricity consumption figures (averaged monthly) for each hour of the day from January 1983 to April 1985 were available from three separate meters: one measuring total farm electricity consumption, a second measuring electricity for milk cooling, and a third measuring electricity for water heating. Due to meter equipment failures and other complications, not all data were collected for each farm.

Other survey data were also available to help explain electrical consumption for each farm. This information included horse power and wattage ratings for large machinery, annual milk production, and the type of technology the farmer used in milking. The engagement times of electrically intensive activities, such as milking and feeding were also reported, and they help explain the relative location of the load curve, which peaks at milking time.

The data contain no information on the price paid for electricity or the price received per hundred weight of milk. Prices should play a major role in any demand study, and given the wide distribution of these farms throughout Wisconsin and parts of Minnesota, it is highly likely that the prices the farmers faced were considerably different. Unfortunately, there is no way to know how the lack of price information affects the estimated load shapes in what follows. Although the differential price data would have improved the regression results for the 26 farms, little would be gained in applying the results to New York farm data where prices were not available either. Because none of the prices would have varied by time of day, one might expect prices to have only shifted the load curve up or down, with little effect on its relative shape.

To gain a better understanding of the data and the shapes of the load curves, a graph for a representative farm milking 55 cows corresponding to its September consumption is illustrated in figure 4.2. Electricity consumption has a bimodal distribution throughout the day because farmers generally milk twice a day.

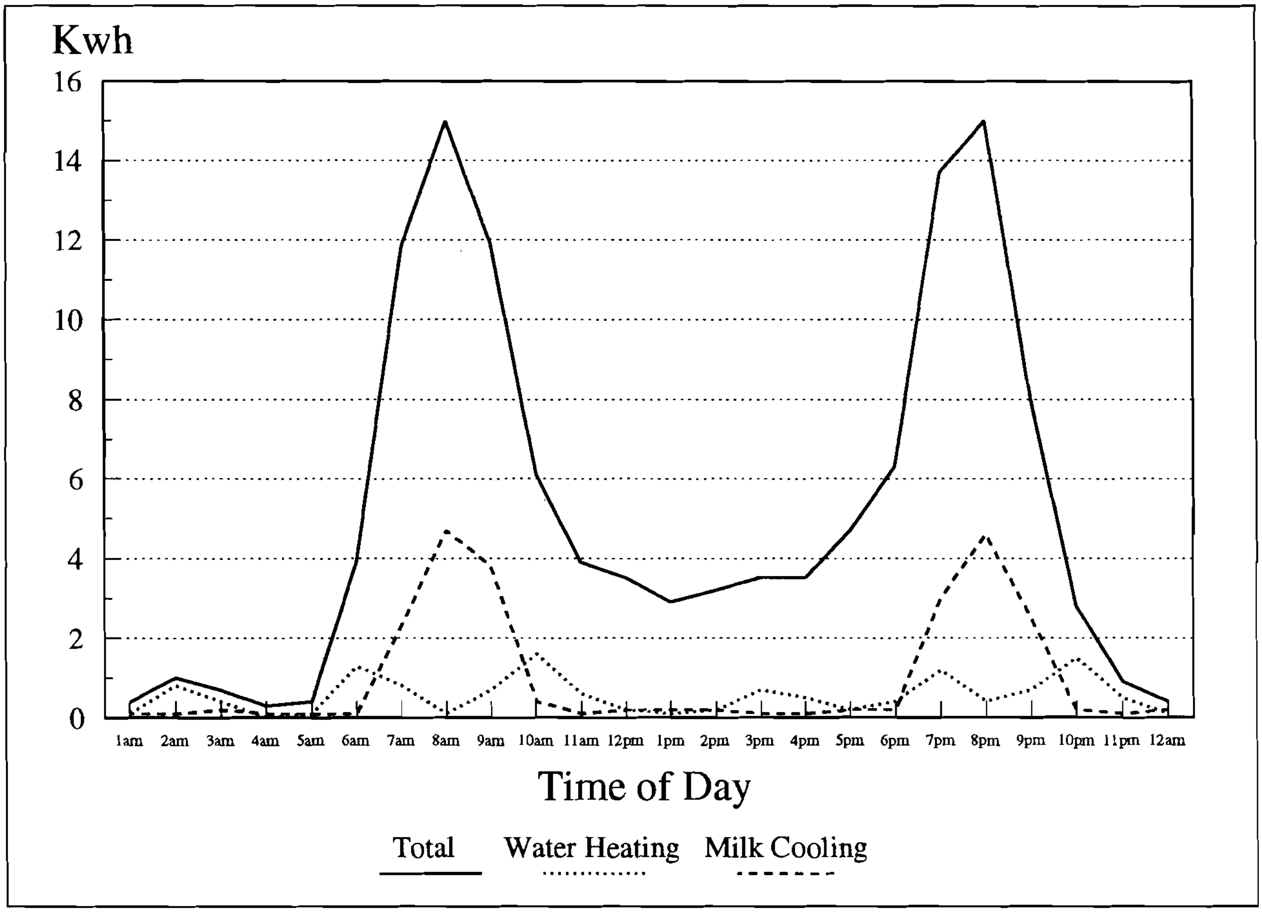

Figure 4.2 Total, water heating and milk cooling September load curves for 55 cow farm.

Empirical Analysis

In this analysis, the cubic spline regression model is applied to estimate the parameters needed to derive load curves corresponding to total electricity consumption and the two end uses for each season. Consumption by end use is of interest to utility personnel as utilities have increasingly placed more emphasis on end-use consumption in forecasting future loads. For this analysis specifically, knowledge of end-use consumption for milk cooling and water heating allows for a more detailed analysis of the effects of adopting conservation measures.

The model is applied directly for total and milk cooling electricity consumption. However, examination of the water heating load curves revealed that its shape could not be explained well by the survey data. Consequently, an alternative method was used in which the water heating load curve was derived indirectly by first constructing a residual load curve (e.g. subtracting electricity used for milk cooling and water heating from the total electricity consumption). The shape of this residual load curve is dictated mainly by the use of vacuum pumps, feeding and cleaning equipment, and lighting. In general, this load shape is more explainable by the survey data than the water heater and leads to better second-stage results. So instead of estimating the model for the three measured meters, it was estimated for total, milk cooling and residual electricity consumption. The water heating load curve could then be constructed by subtracting the residual and milk cooling from the total.

Knot Location

Before the first-stage regressions could be performed, the knot locations had to be chosen. The theory of knot locations is concerned more with numerical analysis than with statistics. However, a simple rule of thumb states that there should be no more than one critical point and one inflexion point between two knots since a cubic polynomial is capable of, at most, two turns (Poirier, 1976, p.152). In the ensuing analysis, even this simple rule is difficult to follow since farmers milk at different times, thus shifting the location of these relative critical points and inflexion points. Therefore, we somewhat arbitrarily chose the knots at 5:00am, 8:00am, 11:00am, 2:00pm, 5:00pm, 8:00pm and 12:00pm.[14] The two-knot locations at 5:00am and 5:00pm occur prior to the start of most milking. This minimizes some of the potential difficulties from having the load curve shift through the knot locations.

First-Stage Regressions

The model presented here differs from an earlier model of Hendricks, Koenker, and Poirier (1979). In their model, the first-stage regression was performed only once for each residential customer. This was accomplished by stacking all of the data for each particular household and performing one first-stage regression. To account for seasonal effects and other factors that would alter the load shape from day to day, appropriate dummy variables were

[14]The W matrix for knots located at these hours can be found in appendix IV.

augmented to the W matrix. As with the other estimated coefficients, the coefficients for these dummy variables were then used as dependent variables in separate second-stage regressions to determine how they differed across households.

This strategy was not possible for our analysis because data are available for only 26 dairy farms. Furthermore, some of these farms lack so much data that it was not possible to construct seasonal dummy variables, thus leading to a singular augmented W matrix. Consequently each load curve is treated as an individual observation and seasonal adjustments are accounted for by using dummy seasonal variables in the second-stage regression. The implication with this approach is that the seasonal effects are assumed to be the same for all farms regardless of size.

After removing missing observations (load curves in effect) and fabricating the residual load curve, 563 first-stage regressions were estimated for total electricity consumption, 399 for milk cooling and 361 for residual. The regressions for total consumption performed the best, with R-square measures consistently in the 90's or high 80's. The milk cooling curves and residual curves also resulted in R-square measures falling mostly in the high 80's. To illustrate, table 4.1 contains the first-stage regression results for five representative farms, all of which correspond to total electricity consumption during the month of June; they illustrate how the estimates correspond to the farm's electricity use at the knot.

Table 4.1 First-stage regression results for total electricity load curve.

	Number of Cows				
Knots	34	50	70	84	99
5:00am	0.800 (1.4)	1.467 (1.9)	1.474 (0.8)	5.247 (2.5)	7.876 (5.5)
8:00am	4.925 (7.6)	6.446 (7.3)	8.659 (4.4)	21.252 (9.2)	17.770 (11.1)
11:00am	5.697 (8.6)	3.089 (3.4)	10.694 (5.3)	8.396 (3.5)	5.038 (3.1)
2:00pm	0.163 (0.2)	2.869 (3.2)	-1.909 (-0.9)	6.116 (2.6)	-0.243 (-0.1)
5:00pm	1.464 (2.2)	4.700 (5.3)	7.683 (3.9)	9.820 (4.2)	13.699 (8.5)
8:00pm	6.154 (10.2)	4.399 (5.3)	8.300 (4.5)	20.760 (9.6)	13.894 (9.3)
12:00pm	1.714 (3.0)	3.107 (3.9)	0.682 (0.4)	1.724 (0.8)	-0.159 (-0.1)
R^2 (t-ratios)	0.94	0.91	0.84	0.93	0.95

Figure 4.3 plots the estimated load curves for the farms milking 34, 70, and 99 cows respectively. These load curves were formed by multiplying the estimates by the W matrix found in appendix IV. At the knots: 5:00am, 8:00am, 11:00am, 2:00pm, 5:00pm, 8:00pm, and 12:00pm, the load curves pass through the estimates.[15]

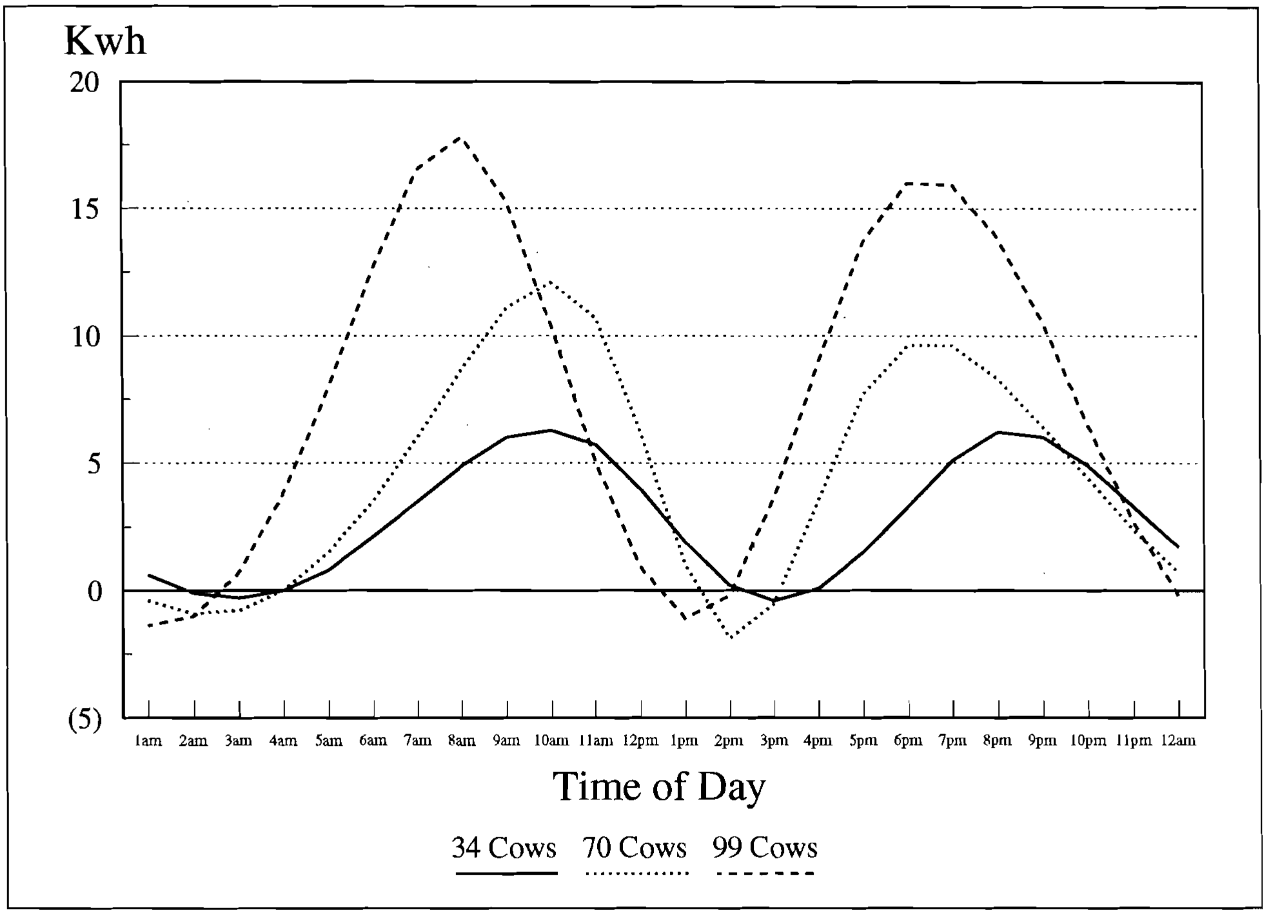

Figure 4.3 First stage load curves for farms milking 34, 70, and 99 cows.

Second-Stage Regression

Once the first-stage regressions are obtained for total, milk cooling, and residual electricity use, the next step is to carry out the second-stage regressions. Assuming that the first-stage estimates are linear functions of the farm characteristics reported in the survey, OLS can be applied.

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[15]Since these first-stage regressions essentially involve time-series analysis, there is always concern over autocorrelation in the error structure. This issue was investigated, but in the final analysis, the OLS regressions were selected. The basis for this selection is given in appendix V.

The second stage entails 21 individual regressions, one corresponding to each of seven knots for each of three end uses: total, milk cooling and residual electricity use. The basis for the functional form and choice of variables is the same as that used to derive the conditional demands in the previous chapter: the level of demand at the knots is determined primarily by the stock of machinery and characteristics of the farm. At some hours these factors may have a major role, while at other hours they may not. Variables are restricted to zero when it is hypothesized that their effects on electricity consumption for that particular knot are negligible.

Farmers use one of three types of milking systems: parlor, pipeline, or bucket. Dummy variables are used for the parlor and bucket systems. Farmers also often milk with two devices available that conserve electricity and chill milk more quickly. A heat transfer uses heat from the compressor motors used in the milk cooling process to help in the heating of water. These devices save electricity since the element in the water heater no longer has to run as much. An icebank builds up ice prior to milking and acts as a pre-coolant before the milk enters the bulk tank cooler. Many farmers use ice banks since they can improve milk quality by chilling it quicker. Dummy variables for these devices are used in the analysis as well (Ice Bank and HT). Since the effectiveness and intensiveness of use for these two devices is a function of farm size (i.e. a large farm operates its milk cooler longer, giving off more heat for which the heat transfer can utilize), cross product terms with the production of milk in thousands of pounds for these two devices are also used. The horsepower of the bulk milk cooler and vacuum pump are included in the regression to isolate the effects of different-sized motors across farms. The number of ventilation fans on the farm is also included as a regressor.

To account for any unexplained variation resulting from unspecified equipment, the milk production in thousands of pounds is included. Dairy farms use electricity to light their barns in the winter and for cleaning and feeding purposes. Although data for these end uses were reported in the survey, there is good reason to believe that electricity used for these end-use purposes is correlated with milk production. For example, farms producing more milk generally have larger barns, require more lighting, use larger feed equipment motors, and are required to transport feed farther distances. To account for economies of size or scale, the square of milk production is also included.

To pick up variation in the level of electricity caused by farmers milking at different times, the milking times and the square of the milking times are included (AM, PM, Square AM, Square PM). Finally, seasonal dummies attempt to reflect seasonal variation (Spring, Summer and Fall).

Table 4.2 gives results for the second-stage regression corresponding to total electricity.[16] At the 12:00am knot most of the variables are restricted to zero, reflecting the fact that activity is minimal in the middle of night. In addition the time shift variables, as well as the machinery variables, are restricted to zero where appropriate. As indicated by the squared milk production term, there does not seem to be significant economies of scale. For some knots, there appears to be diseconomies of scale are present. As farms get larger with respect to milk production, they use increasingly more electricity. The second-stage regressions for milk cooling and residual are similar to that for total (tables 4.3 and 4.4). However, variables that it is thought will not affect electricity consumption for these two end uses (i.e. horsepower of vacuum pump) are not included.

When these regression equations are applied to data with farm characteristics, the load curves for total, milk cooling and residual electricity consumption may be formed for a given farm and season. The water heater load curve can then be formed by subtracting from the total the consumption due to milk cooling and residual at each hour of the day.

5. ANALYSIS OF RATES

This section uses the econometric results from both the previous two sections to estimate how time-of-use rates are expected to affect farmers' electricity costs throughout New York State. To begin, we describe the different time-of-use rates either currently in use or proposed by the major upstate New York utilities. Next, we describe a data set containing a representative sample of New York dairy farms used in the analysis. A methodology for combining the estimated aggregate demand and load shapes to analyze the effects of switching to time-of-use rates is then discussed. The different rates are applied to the sample representative farms and statistics are presented to illustrate how the electricity bills are expected to change. Finally, we discuss how farms differentiated by size, milking technology and other relevant factors are affected within each utility.

Selected New York State Time-of-Use Rate Schedules

The financial effects of time-of-use rates are analyzed for four New York State electric utilities: Niagara Mohawk Power Corporation (NMPC), Rochester Gas and Electric (RG&E), Central Hudson Gas and Electric (CHG&E), and New York State Electric and Gas (NYSEG).

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[16] N = 469 (the number of observations in the second-stage regression) does not correspond to the 563 first-stage regressions due to missing observations on the independent variables.

Table 4.2 Second-stage regression coefficients for total electricity.

	Node						
	12:00am	5:00am	8:00am	11:00am	2:00pm	5:00pm	8:00pm
Intercept	197.152 (3.1)	-34.103 (-2.2)	65.755 (4.1)	-3.853 (-0.4)	67.485 (4.4)	-428.777 (-3.0)	-375.723 (-4.8)
Milk	4.25E-03 (7.4)	1.05E-03 (0.7)	1.99E-03 (1.3)	-2.16E-04 (-0.2)	3.85E-03 (3.0)	-9.29E-04 (-0.9)	-2.75E-03 (-4.8)
Square Milk	-8.55E-07 (-3.2)	2.45E-06 (3.8)	1.76E-07 (0.3)	6.89E-10 (0.0)	1.02E-06 (1.9)	3.19E-06 (5.6)	2.12E-06 (7.5)
Parlor	**	-2.735 (-8.8)	0.352 (1.1)	-1.712 (-10.9)	0.984 (4.4)	-0.533 (-1.7)	-0.229 (-1.5)
Bucket	**	-2.088 (-4.3)	1.692 (3.5)	-0.945 (-3.2)	-0.827 (-1.9)	-3.134 (-9.0)	-1.346 (-7.3)
Milk Cooler HP	**	**	0.015 (0.2)	0.061 (1.2)	-0.048 (-0.7)	0.239 (3.8)	0.032 (0.9)
Ice Bank	-0.336 (-0.9)	0.905 (1.4)	1.617 (2.8)	-1.059 (-3.1)	-1.278 (-2.3)	2.506 (4.7)	-8.05E-03 (-0.0)
Ice Bank*Milk	-5.13E-04 (-0.8)	-2.23E-03 (-1.8)	4.03E-04 (0.4)	3.94E-03 (5.8)	3.88E-03 (3.7)	-2.96E-03 (-2.8)	4.03E-03 (6.9)
HT	-1.01E-10 (-0.0)	-2.042 (-3.8)	1.133 (2.1)	-2.223 (-6.6)	**	-2.549 (-4.3)	-0.045 (-0.1)
HT*Milk	**	1.12E-03 (2.2)	-2.04E-03 (-3.9)	2.56E-03 (7.8)	**	1.33E-03 (2.3)	1.34E-04 (0.4)
Vacuum Pump HP	**	0.534 (8.2)	0.726 (12.1)	**	**	0.314 (4.5)	-0.048 (-1.3)
Number of Fans	**	**	0.150 (2.1)	-0.037 (-0.8)	-0.278 (-4.3)	0.227 (3.4)	**
AM	**	13.020 (2.5)	-24.202 (-4.5)	2.138 (0.6)	-20.222 (-3.9)	**	**
Square AM	**	-1.118 (-2.6)	2.152 (4.7)	-0.206 (-0.7)	1.538 (3.5)	**	**
PM	-21.499 (-2.9)	**	**	**	**	47.463 (2.9)	42.229 (4.8)
Square PM	0.586 (2.8)	**	**	**	**	-1.304 (-2.8)	-1.179 (-4.7)
Spring	-0.015 (-0.1)	-0.042 (-0.2)	-0.883 (-4.3)	-0.022 (-0.2)	-0.364 (-1.8)	-0.100 (-0.5)	-0.171 (-1.7)
Summer	-0.640 (-4.3)	-0.399 (-1.6)	-1.536 (-6.9)	-0.203 (-1.5)	-0.512 (-2.4)	-0.335 (-1.7)	-0.787 (-7.4)
Fall	-0.446 (-2.9)	-0.624 (-2.5)	-1.277 (-5.6)	-0.404 (-2.9)	-1.049 (-4.7)	-0.508 (-2.5)	-0.475 (-4.3)
N	469	469	469	469	469	469	469
R^2	.66	.85	.69	.46	.71	.89	.63
(t-ratios)							

Table 4.3 Second stage regression coefficients for milk cooling.

	Node						
	12:00am	5:00am	8:00am	11:00am	2:00pm	5:00pm	8:00pm
Intercept	158.015 (6.5)	-12.485 (-1.8)	-2.426 (-0.4)	0.998 (0.3)	-1.182 (-0.3)	286.227 (5.6)	2.868 (0.1)
Milk	1.41E-03 (6.4)	1.89E-03 (3.2)	-3.28E-04 (-0.6)	7.23E-04 (2.6)	4.26E-04 (1.1)	2.92E-03 (6.3)	-2.60E-04 (-1.3)
Square Milk	-5.31E-07 (-5.3)	5.26E-08 (0.2)	5.13E-07 (2.2)	-4.18E-07 (-3.4)	5.52E-08 (0.3)	-4.57E-07 (-2.2)	2.45E-07 (2.6)
Milk Cooler HP	0.039 (2.5)	0.094 (2.4)	0.116 (3.3)	0.024 (1.3)	0.092 (3.7)	0.025 (0.8)	-0.034 (-2.3)
Ice Bank	0.296 (2.0)	0.354 (1.0)	0.218 (0.7)	-0.303 (-1.8)	-0.208 (-0.9)	1.293 (4.2)	-1.87E-03 (-0.0)
Ice Bank*Milk	-1.04E-03 (-3.7)	-1.76E-03 (-2.6)	1.09E-03 (1.8)	1.80E-03 (5.7)	4.32E-04 (1.0)	-3.40E-03 (-5.7)	1.40E-03 (5.3)
AM	**	4.139 (1.7)	0.293 (0.1)	-0.634 (-0.6)	0.826 (0.5)	**	**
Square AM	**	-0.344 (-1.7)	0.021 (0.1)	0.069 (0.7)	-0.106 (-0.8)	**	**
PM	-17.821 (-6.5)	**	**	**	**	-33.040 (-5.7)	-0.632 (-0.2)
Square PM	0.501 (6.4)	**	**	**	**	0.951 (5.8)	0.027 (0.4)
Spring	0.060 (1.3)	0.305 (2.5)	-0.158 (-1.4)	-0.062 (-1.1)	0.025 (0.3)	0.242 (2.4)	-0.027 (-0.6)
Summer	0.124 (2.2)	0.561 (4.0)	0.113 (0.9)	0.107 (1.6)	0.152 (1.7)	0.676 (5.8)	0.095 (1.9)
Fall	0.075 (1.3)	0.253 (1.8)	-0.090 (-0.7)	0.022 (0.3)	0.036 (0.4)	0.203 (1.7)	-6.07E-03 (-0.1)
N	388	388	388	388	388	388	388
R^2	.45	.59	.28	.35	.36	.66	.47
(t-ratios)							

Central Hudson Gas and Electric allows its customers to choose among three different rates. The NYSEG rates are only preliminary, subject to approval by the New York State Public Service Commission when this study began. The other three utilities were all in the process of phasing in time-of-use rates for their larger customers, with smaller customers exempt because of the expense of installing sophisticated meters (table 5.1).

Table 4.4 Second stage regression coefficients for residual electricity.

	Node						
	12:00am	5:00am	8:00am	11:00am	2:00pm	5:00pm	8:00pm
Intercept	-143.267 (-2.5)	-66.000 (-4.1)	-12.641 (-1.1)	-14.696 (-1.8)	-128.902 (-1.4)	-1141.053 (-9.0)	-191.276 (-3.6)
Milk	2.79E-03 (6.0)	-5.74E-03 (-4.2)	1.85E-04 (0.2)	7.10E-05 (0.1)	4.54E-03 (5.7)	-4.07E-03 (-4.1)	-8.68E-04 (-2.1)
Square Milk	-2.05E-07 (-0.9)	3.64E-06 (6.0)	-7.74E-07 (-1.8)	1.06E-07 (0.4)	-4.03E-07 (-1.0)	4.02E-06 (8.0)	6.47E-07 (3.0)
Parlor	**	-0.684 (-2.6)	0.234 (1.3)	-0.443 (-3.6)	0.094 (0.5)	-0.409 (-1.9)	0.033 (0.4)
Bucket	**	-1.934 (-3.3)	0.538 (1.3)	-0.267 (-1.0)	-0.144 (-0.4)	-1.717 (-3.7)	-0.624 (-3.2)
Vacuum Pump HP	**	0.352 (5.9)	0.373 (8.8)	**	**	0.143 (2.5)	-0.022 (-0.9)
Number of Fans	**	0.513 (6.6)	0.479 (8.7)	0.196 (5.3)	-0.040 (-0.8)	0.190 (2.6)	0.112 (3.7)
AM	**	23.986 (4.3)	3.665 (0.9)	4.942 (1.8)	**	**	**
Square AM	**	-2.064 (-4.4)	-0.274 (-0.8)	-0.404 (-1.8)	**	**	**
PM	16.884 (2.6)	**	**	**	15.978 (1.5)	129.453 (9.0)	21.515 (3.5)
Square PM	-0.496 (-2.6)	**	**	**	-0.490 (-1.7)	-3.660 (-9.0)	-0.601 (-3.5)
Spring	-0.062 (-0.5)	-0.173 (-0.7)	-0.490 (-2.6)	-0.026 (-0.2)	-0.365 (-2.0)	-0.219 (-1.0)	-0.213 (-2.3)
Summer	-0.741 (-5.1)	-1.055 (-3.5)	-1.256 (-5.9)	-0.374 (-2.5)	-0.954 (-4.6)	-0.944 (-3.7)	-0.843 (-7.8)
Fall	-0.585 (-3.9)	-0.916 (-2.9)	-1.012 (-4.6)	-0.455 (-2.9)	-1.083 (-5.1)	-0.750 (-2.8)	-0.590 (-5.3)
N	350	350	350	350	350	350	350
R^2	.60	.71	.52	.34	.65	.73	.43
(t-ratios)							

The TOU rate schedules for these four utilities are given in figures 5.1 through 5.4; the rates reflect differences in peak demands by season and by time of day. For example, three of the utilities have peak, shoulder and off-peak rates. Niagara Mohawk also has an off-season rate, while Rochester Gas and Electric distinguishes between rates for its summer and winter peaks. The fourth utility, Central Hudson, has only peak and off-peak periods. The various peak, shoulder, and off-peak charges reflect in part the differences in marginal costs of producing energy.

Table 5.1 Eligibility thresholds for time-of-use rates.

Utility	Minimum Annual Kwh Usage for Mandatory TOU Rates
Central Hudson	15-20,000 Kwh*
Niagara Mohawk Power Corporation	30,000 Kwh
New York State Electric & Gas	42,000 Kwh
Rochester Gas & Electric	24,750 Kwh

*Actual Kwh threshold is based upon a summer monthly usage of at least 1,700 Kwh per month. This range provides an approximation.
Source: Middagh, et. al., 1991.

An important consideration in examining the effects of TOU rates is the proportion of the day and season to which the various rates apply. For example, one might expect the implications of the rate for the Central Hudson region to be significant because 36 percent of each day of the year, excluding weekends, is on peak. For Niagara Mohawk, 50 percent of the hours in a year are off-season, while 7 percent, 10 percent, and 33 percent of the hours are on-peak, on-shoulder, and off-peak, respectively. Given that the off-peak and off-season rates are much lower than the flat rate, this seems to indicate that customers located in the Niagara Mohawk service territory might be better off in terms of the charge for energy under time-of-use pricing. The total effect, however, depends on the distribution of consumption by time of day and the relative size of the two customer charges; these same considerations determine the total effect for the other utilities as well.

Data Used to Analyze Effects of Time-of-Use Rates

To analyze how these different TOU rates are expected to affect farmers' utility bills, the rates are applied to a sample of dairy farms included in the 1987 Farm Management and Energy Survey conducted by the Department of Agricultural Economics, Cornell University, with the assistance of the New York State Statistical Reporting Service. This was an enumerative survey in which 1,068 farmers located throughout upstate New York were interviewed to compile statistics on the characteristics of their farm affecting energy utilization. These data are much more detailed than either the data from the small sample of Wisconsin farms, or the 1988 Rural Household and Farm Energy Survey data set described earlier. In particular, the 1987 survey

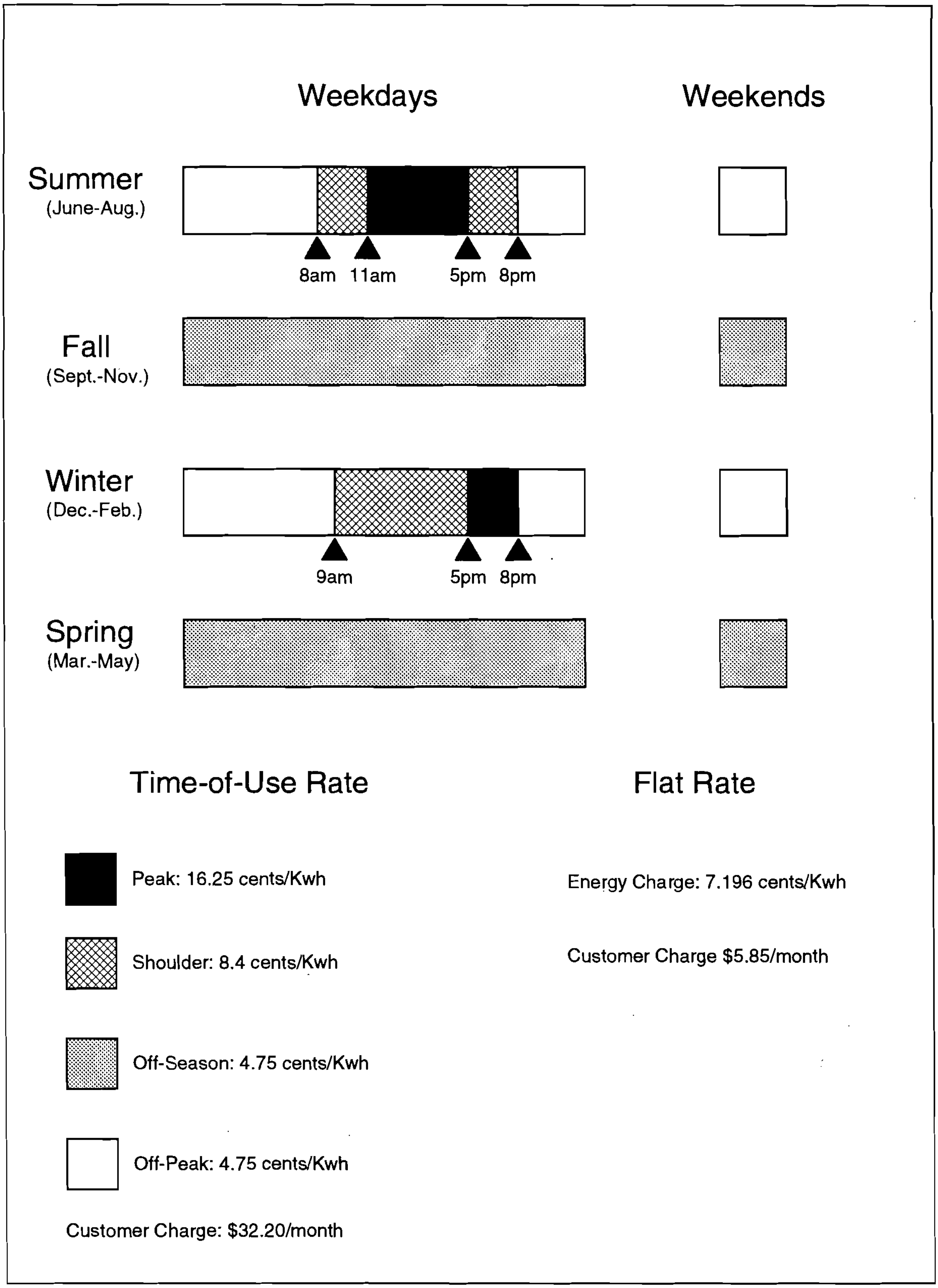

Figure 5.1 Niagara Mohawk Power Corporation time-of-use rate.

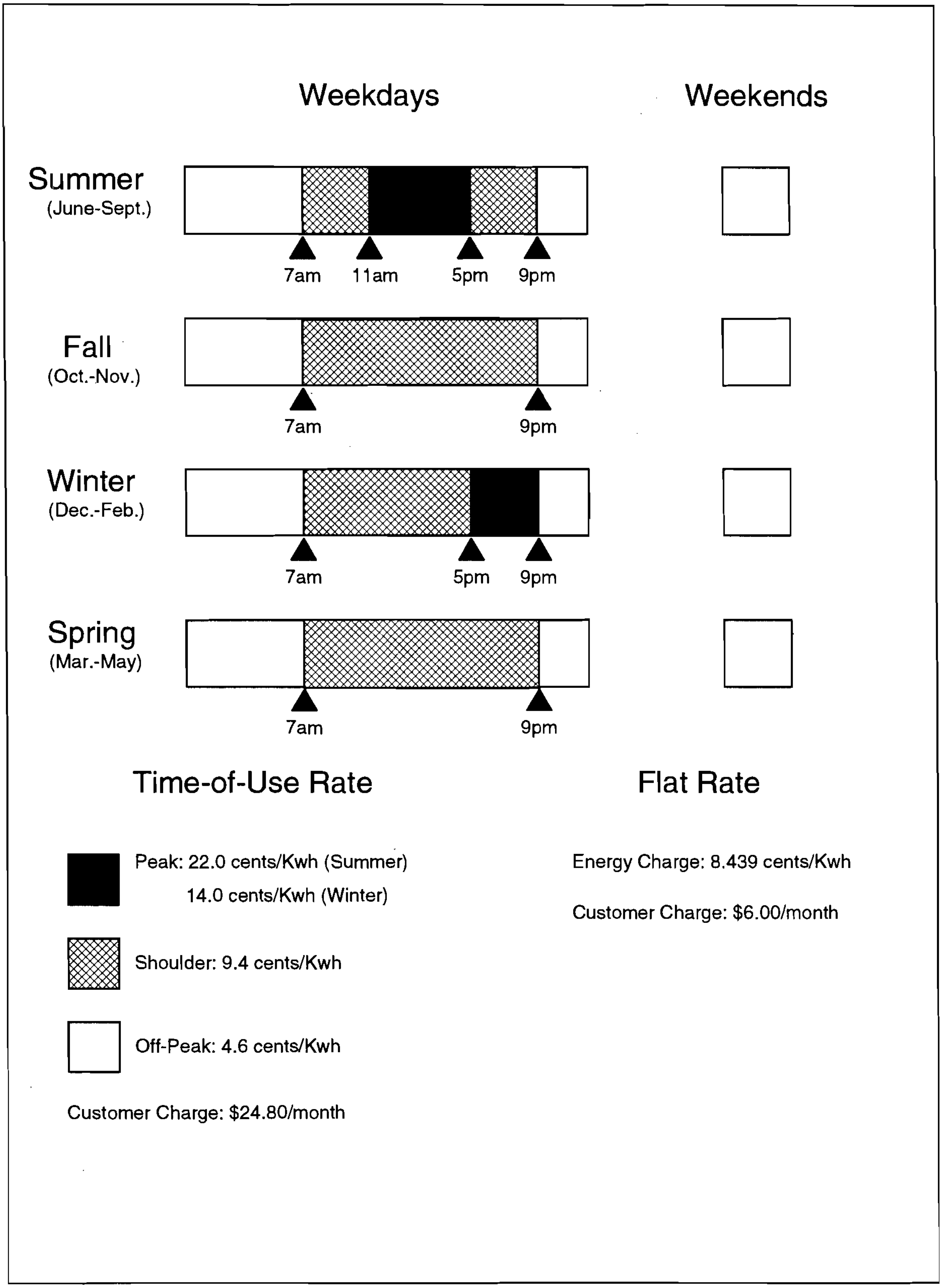

Figure 5.2 Rochester Gas and Electric time-of-use rate.

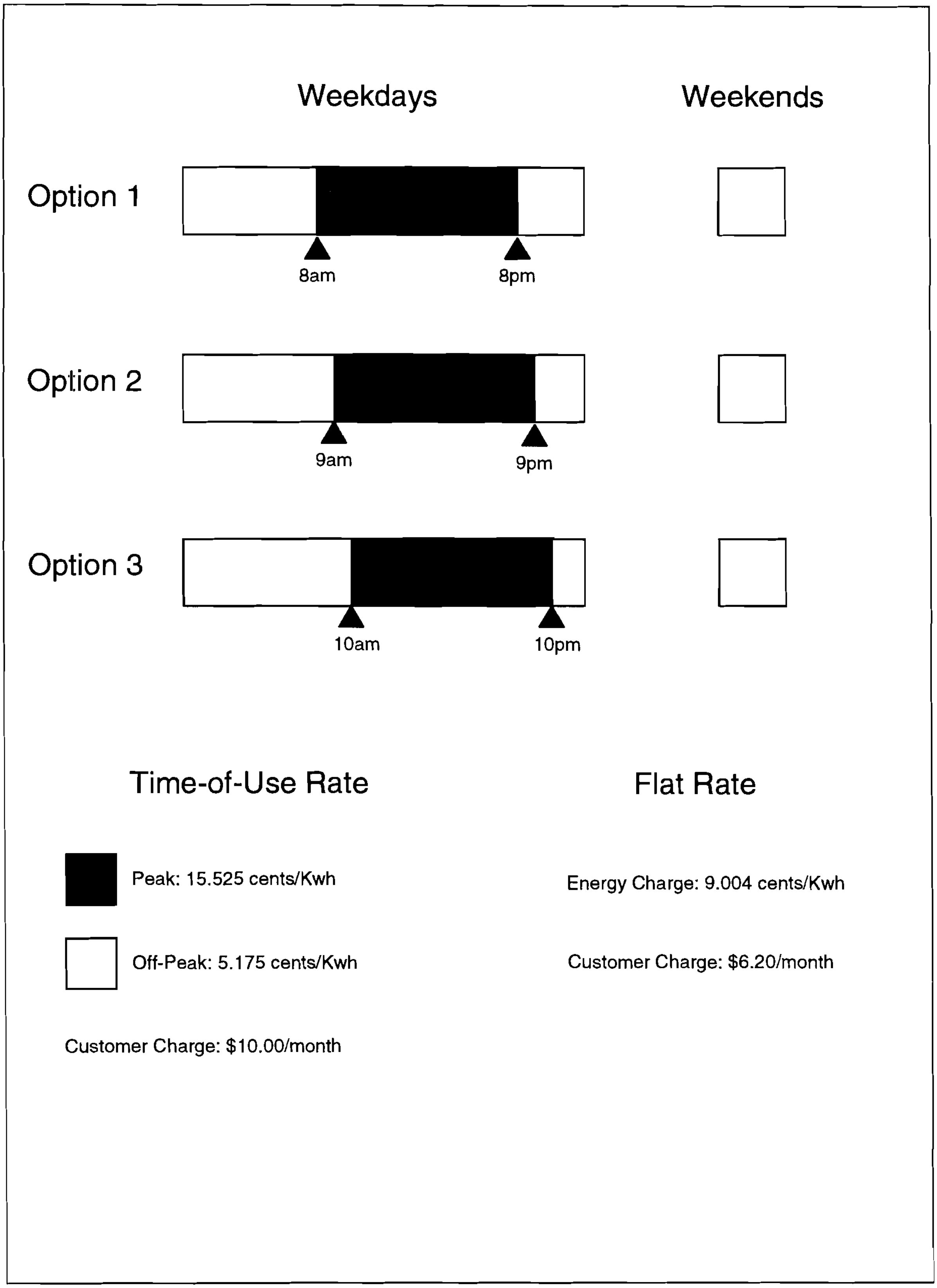

Figure 5.3 Central Hudson Gas and Electric time-of-use rate.

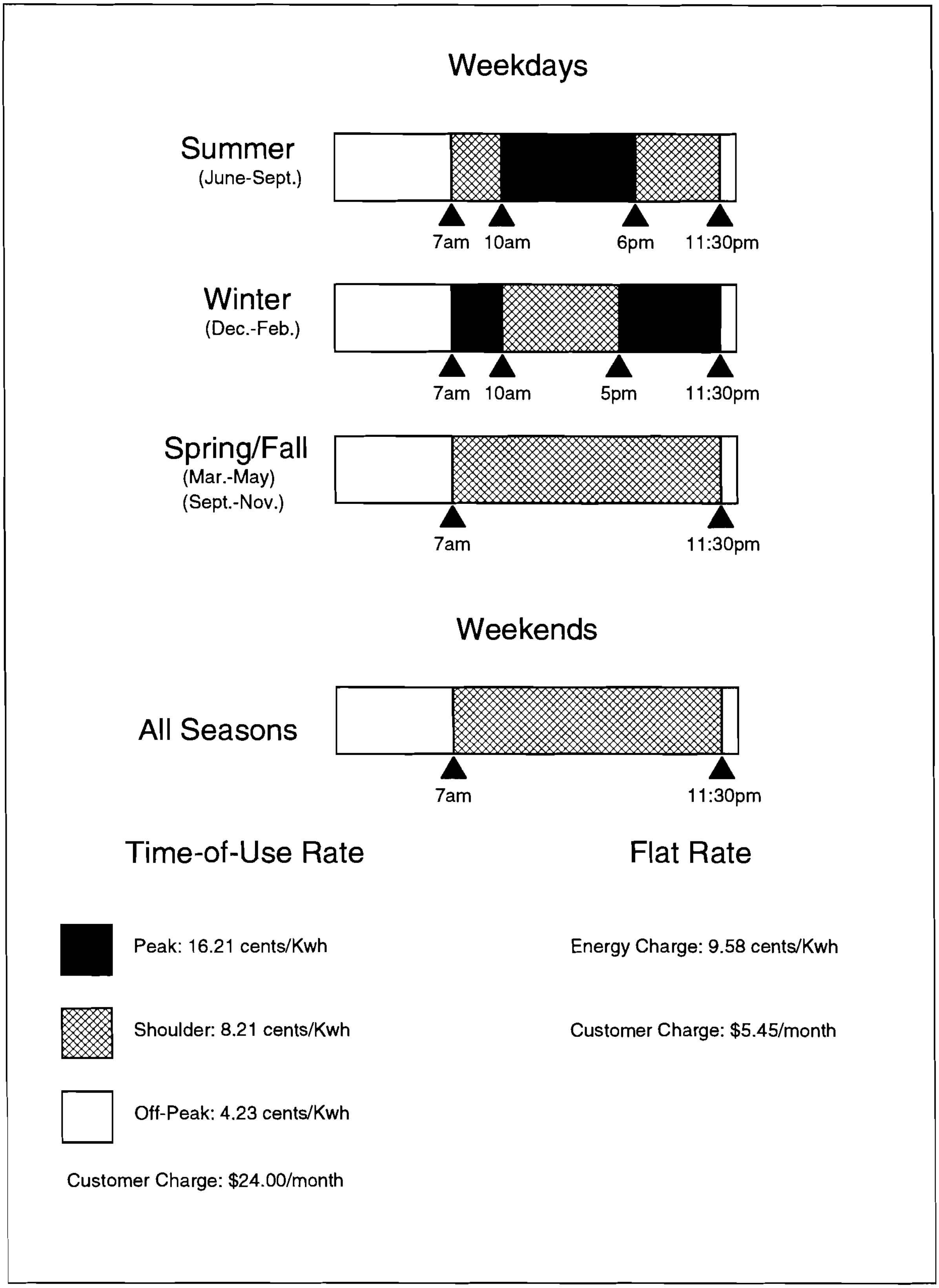

Figure 5.4 Preliminary New York State Electric and Gas time-of-use rate.

includes data on important electrical machinery and the timing of critical farm operations such as milking and feeding, but as stated above, it does not include information on the total consumption of electricity, nor on the daily electricity load shapes as do the Wisconsin data. Furthermore, it includes no separate observations on rural non-farm households as does the 1988 survey data. Thus, these latter two data sets were needed to estimate the relationships discussed in sections 3 and 4.

Once the Wisconsin data and the 1988 survey data have been used to estimate mathematical relationships for daily load shapes and separate estimates for the farm and farm household electricity consumption, these relationships can be applied to the data for the farms in the 1987 survey to estimate the effects of the various TOU rates. The 1987 data set has the added advantage of being drawn from the entire upstate New York region. Thus, it is more representative than the 1988 data which include farms only from Niagara Mohawk's service territory. The only disadvantages is that it was a "blind" survey and the locations of the farms are not known. With the exception of the Central Hudson territory, the farms are probably representative of those found in each of the other service territories.

Of the 1,068 farms surveyed, 758 can be classified as dairy farms. As in the analysis of the 1988 data, screening criteria from table 3.2 were used to eliminate outliers. In addition, it was also necessary to limit attention to the farms milking twice a day, producing between 4,000 and 35,000 hundred-weight of milk per year and having a difference between its evening and morning milking time of at least nine hours. These additional requirements were imposed to keep the analysis within the range of the data from which the daily load curves were estimated. Not surprisingly, when the analysis was extended to farms well beyond these ranges, the estimated load curves made little sense.

After removing the farms that did not meet all of the criteria, we were left with 435 farms for the analysis. Table 5.2 provides descriptive statistics for these farms. The numbers in this table can be compared with the numbers of table 3.3 to provide some perspective on the similarity between farms in this data set and farms in the data set used to estimate the conditional demands in section 3.

Milking efficiency for farms in both data sets is about 14,500 pounds per cow, regardless of farm size. The proportions of farms with electric water heaters, heat transfer devices and ice banks/precoolers are within acceptable ranges in each of the herd-size groups.

Table 5.2 Characteristics of dairy farms from 1987 survey.

	Herd Size			
	50 and under	51 - 75	76-100	Over 100
N	99	153	72	111
Avg. herd size	43	63	88	147
Annual CWT production	6,346	9,265	12,805	21,033
Avg. pounds/cow	14,675	14,581	14,504	14,488
Milking Technology				
Bucket	32 (32.3%)	32 (20.9%)	5 (6.9%)	4 (3.6%)
Pipeline	59 (59.6%)	104 (67.9%)	40 (55.6%)	32 (28.8)%
Parlor	8 (8.1%)	17 (11.2%)	27 (37.5%)	75 (67.6%)
Percent with electric water heater	92%	84%	81%	77%
Percent with heat transfer system	19%	37%	47%	65%
Percent with ice bank/precooler	3%	8%	21%	31%
Avg. number of milking units	4	5	6	9

Source: 1987 Farm Management and Energy Survey.

There are some differences worth noting, and are most likely the result of the 1987 survey being targeted at larger farms. First, there appears to be a larger number of farms using parlor technology. In all four herd-size groups, the proportion of parlor farms in table 5.2 are larger than the corresponding proportions in table 3.3. In contrast, the conditional demand data set has a larger proportion of farms using the pipeline technology. Second, there is a higher proportion of large farms, as measured by number of cows, in the sample data set as compared with the conditional demand data set. Despite these minor differences, it is probably reasonable to use equations estimated from the conditional demand data to predict energy use on this sample of representative farms.

Table 5.3 Summary statistics for effects of TOU rates.

	Utility			
	Niagara Mohawk Power Corporation	Rochester Gas and Electric	Central Hudson Gas and Electric (Opt. 2)	New York State Electric and Gas
Average Kwh	51,161	51,161	51,161	51,161
Flat Rate Bill	$3,752	$4,389	$4,681	$4,967
Energy	98.1%	98.3%	98.4%	98.7%
(¢/Kwh)	(7.196)	(8.439)	(9.004)	(9.58)
Fixed	1.9%	1.7%	1.6%	1.3%
(Cust. Charge)	($70)	($72)	($74)	($65)
TOU Bill	$3,452	$4,260	$4,907	$4,597
Energy	88.8%	93%	97.5%	93.7%
(Avg. ¢/Kwh)*	(5.992)	(7.744)	(9.357)	(8.422)
Fixed	11.2%	7%	2.5%	6.3%
(Cust. Charge)	($386)	($298)	($120)	($288)
Average TOU Rate (¢/Kwh)**	5.900	7.491	8.869	8.148
Average Change	-$300	-$129	$226	-$369
Number of Increases	23	77	417	12
Number of Decreases	412	358	18	423
Average Percentage Change	-6.78%	-2.189%	4.66%	-6.69%
(Range)	(-14.1% to 22.2%)	(-9.34% to 16.85%)	(-2.55 to 25.3%)	(-16.6% to 7.6%)
{S.D.}	{4.1%}	{3.15%}	{3.6%}	{3.3%}
Average Increase	4.18%	2.84%	4.90%	2.69%
Average Decrease	-7.39%	-3.27%	-0.82%	-6.96%

* - Average ¢/Kwh is the (TOU Bill - Customer Charge)/Average Kwh

** - Average TOU Rate is the utility's weighted average rate for each hour; its the rate a customer would pay if electricity was distributed uniformly by day and season.

Methodology

One easy way to analyze the effects of time-of-use rates would be to apply the different rates to simulated load curves using the spline estimates from section 4. In doing this, we would be assuming that the total electricity consumption for a farm located in New York is the same as a similar farm located in Wisconsin or Minnesota. This may not be the best assumption, so in this section we devise a method which combines the conditional demand equations estimated in section 3 to predict the aggregate annual farm electricity consumption for the 435 sample farms, using the estimated cubic spline functions from section 4 to distribute this predicted demand by season and by time of day. After considerable experimentation with the data, this seemed to present few problems. That is, the major problem was in predicting the level of the load curve and not predicting its shape.

The model incorporating these two estimated relationships that is used to estimate the electric bills under time-of-use electric service requires extensive data manipulation, most of which is done through a program written in the C language. The code is long and detailed and is not reported here. To gain some appreciation for how the analysis was accomplished, a brief description of the program follows. The program deals with each of the 435 farms separately.

The first step is to predict the annual electricity consumption. This is accomplished by multiplying the daily electricity consumption predicted from the estimated equation in table 3.8 by the number of days in the year (365). Values for energy consumption corresponding to the ordinate values at the seven spline knots for each season of the year are also predicted. Defining A_{win} as a seven-element column vector corresponding to the knot ordinate values for winter, each of its elements can be found using the regression results of table 4.2. The seven element column vectors for the three remaining seasons, A_{sprg}, A_{sum} and A_{fall}, can be found by adjusting A_{win} for the appropriate dummy variable[17].

Once this is accomplished, four 24-element column vectors, one corresponding to the load curve for each season, are formed by pre-multiplying these vectors by the W matrix in appendix IV. That is:

$$\begin{aligned} L_{win} &= WA_{win} \\ L_{sprg} &= WA_{sprg} \\ L_{sum} &= WA_{sum} \\ L_{fall} &= WA_{fall}. \end{aligned}$$

[17]The seasonal dummy variables correspond to Niagara Mohawk's TOU seasons (figure 5.1).

For some farms, predicting the load curve was actually accomplished in two steps. This procedure was needed because many of the farms drawn from the sample data set report that they either milk at relatively early hours, such as 3:00am and 3:00pm, or at late hours, such as 10:00am and 10:00pm. These extreme times go well beyond the range of milking times used to estimate the regressions in table 4.2, and experimentation with the data suggested that using these milking times would generate load curves that make little sense. One option would have been to discard these observations and do the analysis for only those farms with milking times within a couple hours of 6:00am and 6:00pm. Instead, for these farms, a simple transformation was made as a first step. Both the morning and evening milking times for the sample are shifted the same number of hours so that the evening milking is 6:00pm, the approximate average for the Wisconsin farms. By assuming that the shape of load curve does not change significantly with respect to milking time, this simple transformation led to reasonable predicted loadshapes. After estimation, these load shapes were shifted back the appropriate number of hours to reflect the actual milking times and reposition the load curve accordingly.

Once the load curves are formed, the next step is to distribute consumption seasonally. To do this, it is assumed that total demand for electricity is distributed in the same proportion as the total consumption estimated from the cubic spline regressions. As stated above, this step adjusts for problems in predicting total load using the Wisconsin data. Mathematically, one can multiply the predicted annual electricity consumption by the proportion of electricity consumed in each season based on the Wisconsin load curves:

$$\mathrm{Kwh}_i = \frac{\mathrm{NUM}_i * \mathrm{Daily}_i}{\sum_{j=1}^{4} \mathrm{NUM}_j * \mathrm{Daily}_j} * \mathrm{Annual\ Kwh}$$

where:

i,j = win, sprg, sum, fall.

Kwh_i = Kwh consumption during season i.

NUM_i = The number of days during season i.

$$\mathrm{Daily}_i = \sum_{hour=1}^{24} L_i[hour]$$

Annual Kwh = Annual electricity consumption based on the conditional demand estimates.

The next step is to determine how much electricity is consumed during each hour of the day for the four load curves. To do this, we make use of the following formula which proportions consumption for each hour:

$$L_i^P[\text{hour}] = \frac{L_i[\text{hour}]}{\text{Daily}_i} * \frac{\text{Kwh}_i}{\text{NUM}_i}$$

With these four load curves that represent for each farm the predicted electricity consumption corresponding to the seasons of the year, it is a simple task to calculate utility bills based on the time-of-use rates for the different utilities.

Empirical Results

This section contains a discussion of how the four different TOU rates would affect farms across the state. For much of the analysis, we consider only option two of Central Hudson Gas and Electric since the other two options are quite similar. Emphasis is placed on the characteristics of each utility's rate that differentiate it from the others.

Table 5.3 contains a number of statistics that help summarize how the different rates can be expected to affect farmers' electricity bills. The information in each column of this table should be interpreted as if all the sample farms were located in the respective utility's service territory. Percentage change is given as:

$$\text{Percentage Change} = \left(\frac{\text{TOU Bill} - \text{Flat Rate Bill}}{\text{Flat Rate Bill}}\right) * 100,$$

and thus, negative numbers indicate savings. The average predicted annual electricity consumption per farm is just over 51,000 Kwh. Because the data did not allow for estimating the consumption response to rate differentials, the average consumption does not vary across utility. Given these consumption estimates, Niagara Mohawk has the lowest average bill under flat rate billing, $3,752, while NYSEG has the highest, $4,967. This is expected since the total bill under flat rate, especially when only a small percentage of it is fixed in the customer charge, is highly correlated with the utility's constant Kwh charge. For all utilities, the fixed customer charge is less than two percent of the electricity bill.

Under time-of-use billing, farms located throughout the NMPC, RG&E and NYSEG service territories would, on average, realize reductions in their electricity bills when compared to the flat rate. The average farm, if located in the NYSEG service territory, can expect to save approximately $369 per year, the largest savings among all the utilities, while if within the RG&E and NMPC territories, these farms can expect to save approximately $129 and $300, respectively. Niagara Mohawk customers would continue to pay considerably less for electricity, $3,452 per year, as compared to NYSEG customers, $4,597 per year, and RG&E customers, $4,260 per year.

These changes represent modest percentage savings on the cost of electricity. For the three utilities, the average savings is just over five percent of the total electricity bill. Further, most of the farms can expect at least some savings. This model estimates that only 23 of the 435 sample farms would realize increases in their electricity bills if they were located within the Niagara Mohawk service territory. Of the 435, only 77 and 12 farms would see their utility bills rise under the TOU rates for RG&E and NYSEG, respectively. In sections below, there is a closer examination of each individual utility and the farms realizing different levels of savings.

Since these are the three utilities that serve much of the dairy producing regions of the State, much of the concern expressed by the farm community and the State Legislature when the TOU rates were announced about four years ago was unfounded. However, at the time the rates were announced, the fixed customer charge for Niagara Mohawk was to have been higher than the one used here. This would have changed the situation somewhat. The importance of the energy charge is discussed in greater detail below.[18]

The situation would not be as favorable for the dairy farms located within the Central Hudson Gas and Electric service territory. If this sample of farms is representative of dairy farms in this service territory, they could expect, on average, about a $226 increase in their electricity bills under Option 2. These increases place them at the top of the four utilities with regards to the cost of electricity, averaging $4,907 per farm. Approximately 96 percent of the farms would see some increase in their bills if they were located in this service territory. Yet, the average increase would be less than five percent, ranging from -2.55 to 25.3 percent.

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[18]The fixed customer charge comprises a larger share of the total bill under time-of-use pricing, averaging just under seven percent across the four rates, as compared with flat-rate pricing, of which the customer charge accounts for about 1.5 percent. Under marginal-cost pricing, which is essentially what time-of-use rates are, these electric utilities would be collecting less in revenue than under flat rate or average-cost pricing. Thus, in an attempt to maintain the revenue neutrality of the rate, electric utilities have been allowed substantial increases in their customer charges. This increased customer charge appears as if it could be regressive against the smaller farms.

Table 5.4 helps explain why farms, if located in the CHG&E territory, would experience significant cost increases while farms, if located in the other service territories, would experience windfall savings. First, about 36 percent of all hours in the year are billed at peak rates for CHG&E, while only 7, 9 and 12 percent are billed at the peak rates for NMPC, RG&E and NYSEG, respectively. The high proportion of peak hours in the CHG&E rate is most likely due to demand by commercial businesses located just north of New York City, a demand which is somewhat invariant with respect to season, but is relatively constant throughout business hours. The situation is amplified when one considers that approximately 40 percent of the electricity used on a farm located in this service territory is billed at peak rates. Although the proportion of electricity billed at peak rates for the other utilities is equal to or slightly larger than the portion of time in peak rate periods, the percentages range only from 7 percent to 14 percent. These are substantially lower than the 40 percent for CHG&E.

In contrast, about 83 percent of the hours in a year are billed at the low cost of 4.75¢ per Kwh for NMPC customers; the same percentage of the electricity consumed by a typical farm occurs during these low cost periods. Farms located in the Rochester Gas and Electric territory also have a large proportion of their energy consumption during off-peak periods, about 50 percent. Where NMPC farms consume only 13 percent of their electricity during the relatively more costly shoulder periods, RG&E customers consume closer to 42 percent on shoulder. This helps explain why RG&E farm customers save considerably less in moving to the TOU rate compared with NMPC customers.

When one considers that 64 percent of the electricity consumed on a NYSEG farm will occur during the shoulder period, it is hard to imagine that savings will be realized when farms move to the new rate. However, unlike Niagara Mohawk and Rochester Gas, which both exhibit higher shoulder period prices than their flat rate prices, the price for NYSEG shoulder period electricity is actually lower than the existing flat rate. This helps to explain the considerable savings that NYSEG customers would realize.

The Effects of Milk Production Level

Table 5.5 illustrates how farms of different herd size would be affected by switching to TOU rates for each of the four utilities. For the NMPC rate, all customers experience some savings by moving to TOU pricing; larger farms receive greater absolute savings. The smallest farms save on average about $97 (2.9 percent), while the largest farms save about $577 (10.3 percent).

Table 5.4 Distribution of hours, Kwh and cost for utilities' time-of-use rates.

	UTILITY											
	Niagara Mohawk Power Corporation			Rochester Gas and Electric			Central Hudson Gas and Electric - Option Two			New York State Electric and Gas		
Rate Period	Hours	Kwh	Cost	Hours	Kwh	Cost	Hours	Kwh	Cost	Hours	Kwh	Cost
Off Season	50.1%	49.4%	34.3%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Off Peak	32.8%	31.0%	21.5%	58.3%	49.4%	27.1%	64.3%	59.9%	32.4%	33.3%	22.1%	10.3%
Shoulder	10.4%	13.0%	16.0%	32.8%	42.2%	47.1%	N/A	N/A	N/A	54.8%	64.0%	58.0%
Peak	6.7%	6.6%	15.7%	8.9%	8.4%	17.9%	35.7%	40.1%	64.8%	11.9%	13.9%	24.6%
Winter	N/A	N/A	N/A	2.9%	4.5%	7.5%	N/A	N/A	N/A	N/A	N/A	N/A
Summer	N/A	N/A	N/A	6%	3.9%	10.4%	N/A	N/A	N/A	N/A	N/A	N/A
Customer Charge	N/A	N/A	12.5%	N/A	N/A	7.9%	N/A	N/A	2.8%	N/A	N/A	7.1%

N/A - Not Applicable.

Table 5.5 Average bill change for different size farms.

Utility	Herd Size: 50 and Under	51 - 75	76 - 100	Over 100
NMPC				
Average Change	-97	-206	-351	-577
Avg. Percentage Change	-2.9	-5.9	-8.3	-10.3
Distribution of Costs/(Kwh)				
Off-season	32% (49%)	34% (49%)	35% (50%)	36% (50%)
Off-peak	21% (32%)	21% (31%)	22% (31%)	22% (30%)
Shoulder	15% (13%)	16% (13%)	16% (13%)	17% (13%)
Peak	14% (6%)	15% (7%)	16% (7%)	17% (7%)
Cust. Chg.	17%	14%	11%	8%
RG&E				
Average Change	-14	-77	-154	-288
Avg. Percentage Change	0.1	-1.7	-3.0	-4.3
Distribution of Costs/(Kwh)				
Off-peak	26% (49%)	27% (49%)	27% (49%)	28% (49%)
Shoulder	47% (43%)	47% (42%)	47% (42%)	48% (41%)
Peak - Win.	7% (5%)	8% (5%)	8% (4%)	7% (4%)
Peak - Sum.	9% (4%)	10% (4%)	11% (4%)	12% (4%)
Cust. Chg.	11%	9%	7%	5%
NYSEG				
Average Change	-145	-272	-416	-673
Avg. Percentage Change	-4.0	-6.3	-7.5	-9.1
Distribution of Costs/(Kwh)				
Off-peak	10% (22%)	11% (23%)	10% (22%)	10% (21%)
Shoulder	55% (63%)	57% (63%)	59% (64%)	62% (66%)
Peak	25% (15%)	25% (14%)	25% (14%)	24% (13%)
Cust. Chg.	10%	8%	6%	4%

Table 5.5 continued.

Utility	50 and Under	51 - 75	76 - 100	Over 100
	Herd Size			
CHG&E - Option 2				
Average Change	130	171	263	362
Avg. Percentage Change	4.1	4.3	5.2	5.3
Distribution of Costs/(Kwh)				
Off-peak	33% (61%)	33% (60%)	32% (59%)	32% (59%)
Peak	63% (39%)	64% (40%)	66% (41%)	66% (41%)
Cust. Chg.	4%	3%	2%	2%

For most of the cases analyzed, electricity consumed in each of the defined rate periods varies a little with respect to farm size. Under the NMPC rate, farms with 50 or fewer cows consume about 32 percent of their electricity during off-peak hours, while farms with greater than 100 cows consume two percentage points less, around 30 percent during off-peak hours. Also, regardless of size, approximately 13 percent of electricity is consumed during shoulder periods.

The same situation exists for RG&E and NYSEG. For RG&E, approximately 49, 42, 5, and 4 percent of the electricity is consumed during the off-peak, shoulder, winter-peak and summer-peak periods, respectively, regardless of farm size. While small farms just about break even, large farms realize a saving of 4.3 percent, mostly due to the fact that the fixed customer change on larger farms is spread over a large volume.

In cases where the proportion of electricity consumed in each of the rate periods is constant across different sized farms, variation in the average percentage change due to energy charges is negligible. For NYSEG, the smallest customers can expect about a 4 percent reduction in their electricity bill, while the largest, a 9 percent reduction. Part of the relatively larger savings for NYSEG is the fact that rates in shoulder periods are lower than flat rates.

Based on the CHG&E rate, farms milking 50 cows or less can expect an increase of $130, just over four percent. For farms with more than 100 cows, however, there is about a 5 percent increase in the annual electricity bill.

Factors Related to Percentage Cost Reductions

In this section, further analysis is conducted to determine if there is any systematic relationship between other characteristics of the farm and the relative change in the electricity bill when farms move to the TOU rate. Many of the characteristics of interest are the same as those used to estimate conditional demand for electricity and distribute it by time of day. These relate to farm size, scheduling of critical operations, milking technology, and the use of energy conservation devices.

Understanding how the characteristics of the farm are related to the relative changes in the customer's electricity bill when moving to TOU rates is a first step toward identifying organizational or other changes that could lead to further savings. These relationships may be of interest to utility personnel in developing DSM programs designed to cut down electricity consumption during peak periods.

This systematic relationship can be determined by regressing the farm characteristics on the percentage change in the electricity bill. Table 5.6 contains definitions for variables initially considered in the analysis.

There are good reasons why each of these variables is believed to play a systematic part in determining the percentage change a farm can expect in switching to TOU rates. For example, a heat transfer system and icebank/precooler both alter the shape of the load curve, thus potentially changing the proportion of electricity consumed during the peak, shoulder or off-peak periods. Heat transfers reduce water heating electricity consumption, and icebanks produce ice prior to milking which is used, in turn, to cool milk before it enters the bulk tank cooler. Because of their different energy intensities, the types of milking system used, whether a parlor, a pipeline or a bucket system, also affect the general daily load shape and are included as regressors.

The times that morning and evening milkings begin are also important. They determine the relative location of the peaks in the daily load curves. In general, energy consumption during peak and shoulder periods will be reduced the later a farmer milks in the evening and the earlier he/she milks in the morning. For most New York utilities the shoulder and peak periods tend to be concentrated towards the middle hours of the day, late afternoon and early evening, while the off-peak periods are found later in the evening and early in the morning.

Table 5.6 Variable definitions used in regression of farm characteristics on percentage change in electric bill and energy charge.

Variable	Definition
Intercept	Intercept Value
HT	Dummy for presence of heat transfer system
Icebank	Dummy for presence of icebank/precooler
AM	Morning milking time
Pounds	Annual milk production in pounds
Sqr. Pounds	Annual milk production in pounds squared
Bucket	Dummy for bucket milking system
Parlor	Dummy for parlor milking system
Pipeline*	Dummy for pipeline milking system
PM	Evening milking time
Elec. H2O	Dummy for electric water heater
Eff. Lights	Dummy for presence of high efficiency lighting
Units	Number of units

* - indicates variables is included in intercept.

As was discussed above, the size of the farm is a major factor in the percentage change a farmer can expect to experience. For this reason, the annual milk production in pounds and the square of annual milk production in pounds are included as regressors. These variables are highly correlated with the number of cows because milk production per cow varies little across the farm size groups. By including a measure of size and size squared, the model should be able to isolate the influence of size on bill savings, much of which occurs due to the fixed charge, and test the extent to which this relationship is increasing with size.

To begin the analysis, the variables of table 5.6 were regressed on the percentage change in the electricity bill for each of the utilities.[19] The estimated results are particularly encouraging,

[19]Because of the relatively large sample size, and the fact that the effect of each utility's rate was calculated for each farm, it was not necessary to pool the data and account for differences in utility rates by using dummy variables.

given the cross-sectional nature of the data. For the relationships involving the total utility bills (Table 5.7), the R^2's range from a high of 0.73 for NMPC to a low of 0.26 for CHG&E, option 2. Most of the t-ratios are above two, and the signs on the coefficients are as expected.

To interpret the results of the regressions, it must be emphasized that actual savings in moving to TOU rates are reflected as negative values of the dependent variables. That is, a five percent savings is -5.0. Therefore, if an independent variable in any of the regressions has a negative coefficient attached to it, an increase in that variable leads to a decrease in the algebraic size of the dependent variable, indicating either a smaller cost increase (e.g. 5.0 to 3.0) or a larger cost savings (e.g. -3.0 to -5.0). For example, farmers located in the Central Hudson region and that choose option (1) on average experience about a 1.86 percentage point decrease in their electricity bill by milking one hour later in the evening.

By controlling for other factors, these results suggest that for NMPC, RG&E and NYSEG cost savings rise up to a certain production level and then begin to decrease (table 5.7). For example, cost savings increase in percentage terms for milk production up to 2.48 million pounds per year for NMPC rates.[20] Beyond this point (approximately 170 cows assuming an average of 14,500 pounds of milk per cow), cost savings begin to decrease in percentage terms. A similar pattern is evident for RG&E and NYSEG, with maximum percentage savings occurring at milk production levels reflecting farm sizes of about 200 cows and 177 cows, respectively. These relationships are consistent with being able to spread the fixed costs over a larger base. The fact that percentage cost savings begin to fall at some point suggests that the effect of fixed costs has been dissipated.

Since one of the reasons TOU rates are introduced is to shift demand to off-peak periods, one obvious strategy for potentially increasing savings under TOU pricing is to shift the schedules of electrically intensive activities. The effects of altering milking times on farm

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There was little reason to retain variables in the initial model specification if the t-ratios were very low. Thus, a second set of models was estimated which restricted the coefficients on the variables with initial t-ratios less than one to be zero. The one exception was that if the t-ratio for either pounds or pounds squared was above one in the initial model, both were retained in the second set of estimates. This strategy verified that the results of the final specifications were extremely insensitive to these restrictions. None of the signs on the coefficients changed, and the magnitudes of the coefficients changed little as well. Table 5.7 contain the regression results for the final model specifications.

[20]These production levels representing the maximum percentage cost savings are calculated by taking the partial derivative of the regression equation with respect to pounds, setting the derivative equal to zero and solving for pounds.

Table 5.7 Estimated relationship between the percentage change in the farmers' utility bills and selected farm characteristics.

	Utility			
Variable	NMPC	RG&E	CHG&E (2)	NYSEG
Intercept	9.77	11.59	22.58	-0.22
	(4.23)	(4.89)	(7.45)	(-0.10)
HT	0.82	0.55	**	**
	(3.58)	(2.34)		
Icebank	0.79	1.57	0.55	**
	(2.49)	(4.91)	(1.27)	
AM	0.46	1.03	2.38	1.67
	(2.73)	(5.98)	(9.77)	(10.28)
Pounds	-0.12E-4	-0.68E-5	**	-7.34E-6
	(-16.76)	(-8.94)		(10.40)
Sqr. Pounds	2.42E-12	1.16E-12	**	1.43E-12
	(11.32)	(5.35)		(7.01)
Bucket	3.25	2.49	**	0.60
	(10.70)	(7.99)		(2.06)
Parlor	**	-0.42	1.61	-0.45
		(-1.53)	(4.12)	(-1.73)
PM	-0.43	-0.78	-1.86	-0.54
	(-2.61)	(-4.57)	(-7.96)	(-3.34)
Elec. H2O	-2.95	-1.93	-0.59	-1.38
	(-10.39)	(-6.67)	(-1.46)	(-5.10)
Eff. Lights	**	**	0.26	**
			(0.76)	
Units	**	0.08	**	0.12
		(1.47)		(2.14)
N	435	435	435	435
R^2	0.73	0.54	0.26	0.61
(t-ratios)				

** - Restricted to zero.

Note: The dependent variable is the percentage change in a farmer's utility bill in moving from the flat rate to the TOU rate. The variable names are given in table 5.6.

savings can be determined through inspection of the coefficients for AM and PM in the various regressions.

For each utility, the AM coefficient is positive, while the PM coefficient is negative (Table 5.7). For example, farms located within the NYSEG region can on average reduce their electricity bill approximately 1.67 percentage points by milking one hour earlier in the morning. These same farms can also save approximately 0.54 percentage points by milking one hour later in the evening. The savings that farmers could realize by changing their milking times are marginal; a three percent savings on a $5,000 electricity bill corresponds to $150. This savings must be compared with the disadvantages of altering the farmers life style and any possible yield losses due to increasing the interval between milking times. Since most farmers seem to set this interval at approximately 12 hours, it appears that there is limited potential for savings by adjusting milking schedules. Any savings in the morning are offset by increases in the evening, and vice versa if the whole milking schedule is shifted to maintain the 12 hour interval between milkings.

The effects of heat transfer systems and icebanks on the savings when switching to TOU pricing can also be analyzed. Initially, heat transfer systems were developed to conserve electricity and icebanks to increase the quality of milk by chilling it quicker. Examination of the coefficients for these two devices from the farm conditional demand estimates (table 3.7), indicates that a heat transfer system saves approximately 2,313 Kwh per year while an ice bank increases electricity consumption about 1,310 Kwh.

While a heat transfer system may be justified as a conservation measure to reduce overall consumption, it is unclear whether they would be an effective demand side management tool designed to shift load and reduce peak period demand, thus leading to customer savings in switching to TOU rates. Inspection of table 5.7 indicates that farms with heat transfers experience smaller percentage savings than those without them. For NMPC and RG&E, farms without heat transfer systems realize on average 0.82 and 0.55 percentage points more savings as compared to those farms with them, respectively. A probable explanation could be that because of milking schedules, heat transfers reduce electricity consumption that occurs mainly during the off-peak and shoulder hours, with little consumption savings during the peak hours.

Icebanks lead to a more even distribution of electricity for milk cooling purposes. Ice is made prior to milking and is used to pre-cool milk entering the bulk tank, and subsequently, lowering the electricity use by the milk cooler. Despite the fact that they lead to overall increases in electricity consumption, this spreading of the load could result in increased savings in moving to TOU rates if a large portion of electricity that would have been consumed by the cooler falls under the utility's peak period. This appears not to be the case for the New York utilities because the signs on the coefficients of the icebank variable are positive, indicating decreased percentage savings (table 5.7).

Finally, to understand the effects of the milking system on moving to TOU rates, one must consider the sign and magnitudes for the parlor and bucket coefficients relative to a pipeline system, which serves as a reference point in the intercept. Although the t-ratios indicate that the coefficients are significant, there seems to be no clear explanation for some of the signs. For NMPC, RG&E, and NYSEG, the positive coefficients indicate that bucket milking systems realize the smallest relative savings, followed by pipeline systems, and the negative coefficients suggest that parlors realize greater savings.

6. SUMMARY AND CONCLUSIONS

In recent years, New York dairy farmers have been concerned about potential increases in energy costs as upstate utilities, under mandate from the New York Public Service Commission, move to TOU rates. This concern stems from a desire on the part of farms to keep milkings at fixed intervals, thus, making it difficult to shift peak load electricity to off-peak hours. For this reason, dairy farmers have raised equity issues and have challenged mandatory time-of-use pricing. Since dairying is a significant component of most upstate New York rural communities, these effects warrant further attention.

The objective of this study is to quantify the effects of TOU electricity rates on dairy farms for a number of upstate utilities, and to determine how they are affected by the characteristics of the farms. This latter objective is of interest since it helps to explain how, if possible, farmers can alter their farm configuration to save on electricity costs under TOU rates.

To accomplish these objectives, it was necessary to estimate electricity consumption by major end use, season and time of day. This was done by combining data from two large data sets containing information on energy use by farms and rural households in New York with a small midwestern data set reporting electricity use on dairy farms by time of day and major end use. First, conditional demand models (models in which the customer's stock of appliances and characteristics of farm and dwellings play a significant part in determining demand) were estimated from a sample of rural houses. These equations were used to estimate farm household demand. Once this was done, household demand was subtracted from the total to get demand on the farm. These estimates were used as the dependent variable in the farm conditional demand equations. These estimates of farm electricity demand were distributed with the help of a cubic spline regression model estimated for total demand and demand by two end uses, water heating and milk cooling, from a small sample of farms for which load curves were available.

Once this estimation was completed, the equations were combined in a complex program written in C, to analyze how time-of-use rates will affect farms in New York. The methodology uses the time-of-day estimates to proportion the predicted electricity consumption based on the conditional demand estimates by season and time of day. Then, load curves are constructed and the electricity bills under TOU pricing and flat rate pricing are calculated assuming that the sample of farms is located in the service territories for each of four upstate utilities.

Contrary to initial concern in the farm community, the findings suggest that, with the exception of the case where farms are assumed to be located within the Central Hudson Gas and Electric service territory, electricity charges would actually decrease on average under TOU pricing as compared to flat rate pricing. For example, if this sample of farms were located in the NYSEG service territory, they could on average expect to save approximately \$369 (6.5 percent) per year, the largest savings among all the utilities. If the farms were within the RG&E and NMPC territories, they could expect to save approximately \$129 (2.2 percent) and \$300 (6.8 percent), respectively. On the other hand, farms located within the Central Hudson region could expect, on average, to experience about a \$226 (4.7 percent) increase in their electricity bills under one of its TOU options. Further, for the three utilities where average savings are positive, there is some variation around the mean, but, in the two service territories with the lion's share of New York's farm customers (NMPC and NYSEG), fewer than five percent of the farms in the sample realized cost increases. Costs would rise for fewer than 20 percent of the farms in the RG&E service territory.

Although these results are reasonable, there are a couple of reasons why they should be interpreted with some care. First, the data used in the estimation procedures exhibited no price variation and could potentially leave some savings (due to shifting load off peak) unaccounted for. Second, the data were drawn from a survey targeted toward larger customers, and may not be completely representative of smaller customers. Despite these limitations, the analysis does contribute importantly to isolating the differential changes in farm electrical costs across service territories where rates are set to reflect different peak loads. It also identifies a "fixed cost" effect that benefits larger farms more than smaller farms. Under time-of-use pricing, utilities increase their customer charge to accommodate higher administrative costs and maintain revenue neutrality for the class. This fixed charge is a smaller percent of the total bill for the larger farms, and hence, allows them to more easily spread it out over total costs.

A simple equation, in which farm characteristics are regressed on the percentage savings in electricity bill for each utility, was estimated to determine how they are related. Because of the "fixed cost" effect, it is not surprising that in these regressions, milk production and milk production squared turn out to be the most significant variables. As these variables increase, so do the percentage savings, except in the case of Central Hudson Gas and Electric rates. Including them in the regression allows the other variables to account for remaining variation in electricity bill changes. Of particular interest is that the signs on the coefficients for morning milking and evening milking are opposite from one another for each utility. This suggests that, given farmers are likely to keep the interval between milkings the same, there are limited opportunities for farmers to shift electricity consumption from peak hours to offpeak hours by changing the timing of milking. The results also suggest that heat transfer systems do not lead to substantive savings under TOU pricing, but, depending on the cost, they might still be recommended as a sound conservation measure because they do reduce yearly electricity use.

As is the case at the conclusion of any single piece of research, one can always point to ways in which the study could be improved and avenues for additional work. Because of the type of detailed energy use data required for a study of this kind, it is not surprising that substantial improvements in the analysis could be made if data could have been collected specifically for this study. Having to rely on three data sets placed some important constraints on the specifications of conditional demand equations and cubic spline regressions. Essentially, independent variables used in the models had to be those common to all data sets. The extent to which the results would have been improved had this not been a constraint is an empirical question that could be resolved only through additional data collection.

Any additional data collection to improve the analysis would also have to include sufficient data on use by time of day to allow for seasonality in the second-stage regressions for the cubic spline models. Thus, load curves for more months and days of the year would be needed. From an economic point of view, however, the major missing link in the analysis was the lack of price variation in the data to accommodate measuring the effects of different prices on electricity demand and the willingness to shift load off peak in response to high prices on peak.

As farms across New York and elsewhere in the country gain experience being on TOU rates, it will become possible to collect the detailed data required to conduct a more comprehensive study of the effects of TOU rates on agriculture. Given the fact that current TOU rate structures seem to imply cost savings to farms ignoring any price response, however, it seems unlikely that the additional cost savings that might accrue to farmers by altering behavior would be large enough to justify major changes in production scheduling. The major interest in more detailed analysis of the effects of TOU rates is likely to be at the request of utilities interested in knowing more about customer response and its implications for rate design to effectively recover costs of operation.

Appendix I

Derivation of Cubic Spline Continuity Conditions

We begin by noting that the second derivative of a third degree polynomial is linear and by defining the second derivatives at the knots as:

$$M_{j-1}=S''(x_{j-1}) \qquad M_j=S''(x_j).$$

By applying the two point equation of a straight line, the second derivative of a cubic spline for any $x_{j-1}\leq x\leq x_j$ $(j=1,2,...,k)$ can be expressed as follow:

$$S''(x)=\left[\frac{x_j-x}{h_j}\right]M_{j-1}+\left[\frac{x-x_{j-1}}{h_j}\right]M_j$$

where $h_j = x_j-x_{j-1}$. Integrating this expression for the second derivative gives:

$$S'(x)=-\left[\frac{(x_j-x)^2}{2h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^2}{2h_j}\right]M_j+C_1.$$

Integrating again to obtain an expression for the function itself gives:

$$S(x)=\left[\frac{(x_j-x)^3}{6h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^3}{6h_j}\right]M_j+C_1x+C_2.$$

Imposing the interpolation requirements $S(x_j)=y_j$ and $S(x_{j-1})=y_{j-1}$ results in:

$$\text{(I.1)} \quad S(x_j)=\frac{h_j^2}{6}M_j+C_1x_j+C_2=y_j$$

$$\text{(I.2)}\quad S(x_{j-1})=\frac{h_j^2}{6}M_{j-1}+C_1x_{j-1}+C_2=y_{j-1}$$

Subtracting (I.2) from (I.1) gives:

$$\frac{h_j^2}{6}M_j-\frac{h_j^2}{6}M_{j-1}+C_1h_j=y_j-y_{j-1}$$

implying:

$$C_1=\frac{y_j-y_{j-1}}{h_j}+\frac{h_jM_{j-1}}{6}-\frac{h_jM_j}{6}.$$

Substituting this value of C_1 into the expression for S'(x) gives:

$$S'(x) = -\left[\frac{(x_j-x)^2}{2h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^2}{2h_j}\right]M_j+\frac{y_j-y_{j-1}}{h_j}+\frac{h_jM_{j-1}}{6}-\frac{h_jM_j}{6}.$$

Rewriting:

$$S'(x) = \left[\frac{h_j}{6}-\frac{(x_j-x)^2}{2h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^2}{2h_j}-\frac{h_j}{6}\right]M_j+\frac{y_j-y_{j-1}}{h_j}.$$

Noting that:

$$\lim_{x\to x_j^-} S'(x) = \lim_{x\to x_j^-} S_j'(x) = \lim_{x\to x_j^+} S_{j+1}'(x) = \lim_{x\to x_j^+} S'(x)$$

for j = 1,2,3...,k-1 and

$$\lim_{x\to x_k^-} S'(x) = \lim_{x\to x_k^-} S_k'(x) = \lim_{x\to x_0^+} S_1'(x) = \lim_{x\to x_0^+} S'(x),$$

and evaluating these one sided limits gives:

$$\lim_{x\to x_j^-} S_j'(x)=\lim_{x\to x_j^-}\left(\left[\frac{h_j}{6}-\frac{(x_j-x)^2}{2h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^2}{2h_j}-\frac{h_j}{6}\right]M_j+\frac{y_j-y_{j-1}}{h_j}\right)$$

$$=\frac{h_j}{6}M_{j-1}+\left(\frac{h_j}{2}-\frac{h_j}{6}\right)M_j+\frac{y_j-y_{j-1}}{h_j}$$

$$=\frac{h_j}{6}M_{j-1}+\frac{h_j}{3}M_j+\frac{y_j-y_{j-1}}{h_j}$$

$$\lim_{x\to x_j^+} S_{j+1}'(x)=\lim_{x\to x_j^+}\left(\left[\frac{h_{j+1}}{6}-\frac{(x_{j+1}-x)^2}{2h_{j+1}}\right]M_j+\left[\frac{(x-x_j)^2}{2h_{j+1}}-\frac{h_{j+1}}{6}\right]M_{j+1}+\frac{y_{j+1}-y_j}{h_{j+1}}\right)$$

$$=\left[\frac{h_{j+1}}{6}-\frac{h_{j+1}}{2}\right]-\frac{h_{j+1}}{6}M_{j+1}+\frac{y_{j+1}-y_j}{h_{j+1}}$$

$$=-\frac{h_{j+1}}{3}M_j-\frac{h_{j+1}}{6}M_{j+1}+\frac{y_{j+1}-y_j}{h_{j+1}}.$$

Setting them equal to each other:

$$\frac{h_j}{6}M_{j-1}+\frac{h_j}{3}M_j+\frac{y_j-y_{j-1}}{h_j}=-\frac{h_{j+1}}{3}M_j-\frac{h_{j+1}}{6}M_{j+1}+\frac{y_{j+1}-y_j}{h_{j+1}}$$

$$h_jM_{j-1}+2h_jM_j+\frac{6(y_j-y_{j-1})}{h_j} = -2h_{j+1}M_j-h_{j+1}M_{j+1}+\frac{6(y_{j+1}-y_j)}{h_{j+1}}$$

$$h_jM_{j-1}+2h_jM_j+2h_{j+1}M_j+h_{j+1}M_{j+1}=\frac{6(y_{j-1}-y_j)}{h_j}+\frac{6(y_{j+1}-y_j)}{h_{j+1}}$$

$$h_jM_{j-1}+2(h_j+h_{j+1})M_j+h_{j+1}M_{j+1}=\frac{6y_{j-1}}{h_j}-\frac{6y_j}{h_j}-\frac{6y_j}{h_{j+1}}+\frac{6y_{j+1}}{h_{j+1}},$$

dividing both sides by $h_j + h_{j+1}$ and defining

$$\lambda_j = \frac{h_j+1}{h_j+h_{j+1}}$$

gives:

$$\frac{h_j M_{j-1}}{h_j+h_{j+1}}+2M_j+\lambda_j M_{j+1}=\frac{6y_{j-1}}{h_j(h_j+h_{j+1})}-\frac{6y_j}{h_j(h_j+h_{j+1})}-\frac{6y_j}{h_{j+1}(h_j+h_{j+1})}+\frac{6y_{j+1}}{h_{j+1}(h_j+h_{j+1})}.$$

$$\text{Noting } \frac{h_j M_{j-1}}{h_j+h_{j+1}} = \frac{(h_j+h_{j+1}-h_{j+1})M_{j-1}}{h_j+h_{j+1}} = \left(1-\frac{h_{j+1}}{h_j+h_{j+1}}\right)M_{j-1} = (1-\lambda_j)M_{j-1}$$

$$\text{and } \frac{-6y_j}{h_j(h_j+h_{j+1}}-\frac{6y_j}{h_j(h_j+h_{j+1})} = \frac{-6y_j h_{j+1}-6y_j h_j}{h_{j+1}h_j(h_j+h_{j+1}}=\frac{-6y_j}{h_{j+1}h_j}$$

implies:

$$(1-\lambda_j)M_{j-1}+2M_j+\lambda_j M_{j+1}=$$
$$\frac{6y_{j-1}}{h_j(h_j+h_{j+1})}-\frac{6y_j}{h_j h_{j+1}}+\frac{6y_{j+1}}{h_{j+1}(h_j+h_{j+1})}.$$

By similar analysis the continuity conditions:

$$(1-\lambda_k)M_{k-1}+2M_k+\lambda_k M_1=$$
$$\frac{6y_{k-1}}{h_k(h_k+h_1)}-\frac{6y_k}{h_k h_1}+\frac{6y_1}{h_1(h_k+h_1)}$$

and

$$(1-\lambda_1)M_k+2M_1+\lambda_1 M_2=$$
$$\frac{6y_k}{h_1(h_1+h_2)}-\frac{6y_1}{h_1 h_2}+\frac{6y_2}{h_2(h_1+h_2)}$$

can be derived.

Appendix II

Derivation of Polynomial Coefficients

Define for $x_{j-1} \leq x \leq X_j$

$$S(x) = a_j + b_j(x-x_{j-1}) + c_j(x-x_{j-1})^2 + d_j(x-x_{j-1})^3.$$

Then

$$S'(x) = b_j + 2c_j(x-x_j) + 3d_j(x-x_{j-1})^2$$
$$S''(x) = 2c_j + 6d_j(x-x_{j-1}).$$

But from the definition of M_j in appendix II:

$$\text{(II.1)} \quad S''(x_j) = 2c_j+6d_jh_j = M_j$$
$$\text{(II.2)} \quad S''(x_{j-1}) = 2c_j = M_{j-1} \rightarrow c_j = \frac{M_{j-1}}{2}.$$

Substituting c_j into the first equation above:

$$M_{j-1} + 6d_jh_j = M_j \rightarrow d_j = \frac{M_j-M_{j-1}}{6h_j}$$

and evaluating S(x) at x_{j-1}:

$$S(x_{j-1}) = a_j = y_j.$$

Evaluating S(x) at x_j, substituting the values for a_j, c_j, b_j and setting equal to y_j gives:

$$S(x_j) = y_{j-1} + b_jh_j + \frac{M_{j-1}h_j^2}{2} + \frac{(M_j-M_{j-1})h_j^3}{6h_j} = y_j.$$

Solving for b_j:

$$b_j = \frac{y_j - y_{j-1}}{h_j} - \frac{M_{j-1}h_j^2}{2h_j} - \frac{(M_j - M_{j-1})h_j^2}{6h_j}$$
$$b_j = \frac{y_j - y_{j-1}}{h_j} - \frac{3M_{j-1}h_j - M_jh_j + M_{j-1}h_j}{6}$$
$$b_j = \frac{y_j - y_{j-1}}{h_j} - \frac{h_j(2M_{j-1} + M_j)}{6}.$$

So for $x_{j-1} \leq x \leq x_j$, $j = 1,2....k$

$$S_j(x) = a_j + b_j(x - x_{j-1}) + c_j(x - x_{j-1})^2 + d_j(x - x_{j-1})^3$$

with
$$a_j = y_j$$
$$b_j = \frac{y_j - y_{j-1}}{h_j} - \frac{h_j(2M_{j-1} + M_j)}{6}$$
$$c_j = \frac{M_{j-1}}{2}$$
$$d_j = \frac{M_j - M_{j-1}}{6h_j}.$$

Appendix III

Representation of S(x) in terms of M

The representation of S(x) in terms of **M**, the vector of second derivatives evaluated at the knots, is required to construct the matrix **W**. This can be accomplished by solving for S(x) from the previous appendix:

$$S(x)=\left[\frac{(x_j-x)^3}{6h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^3}{6h_j}\right]M_j+C_1x+C_2.$$

Substituting the value of C_1 into equation II.2 of appendix II:

$$\frac{h_j^2}{6}M_{j-1}+\left[\frac{y_j-y_{j-1}}{h_j}+\frac{h_jM_{j-1}}{6}-\frac{h_jM_j}{6}\right]x_{j-1}+C_2 = y_{j-1}$$

and solving for C_2:

$$C_2 = y_{j-1}+\frac{h_jM_jx_{j-1}}{6}-\frac{h_jM_{j-1}x_{j-1}}{6}-\frac{(y_j-y_{j-1})x_{j-1}}{h_j}-\frac{h_j^2M_{j-1}}{6}.$$

Substituting C_1 and C_2 into S(x):

$$\begin{aligned}S(x) = &\left[\frac{(x_j-x)^3}{6h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^3}{6h_j}M_j\right]+\frac{(y_j-y_{j-1})x}{h_j}\\ &+\frac{h_jM_{j-1}x}{6}-\frac{h_jM_jx}{6}+y_{j-1}+\frac{h_jM_jx_{j-1}}{6}\\ &-\frac{h_jM_{j-1}x_{j-1}}{6}-\frac{(y_j-y_{j-1})x_{j-1}}{h_j}-\frac{h_j^2M_{j-1}}{6}\end{aligned}$$

$$\begin{aligned}=&\left[\frac{(x_j-x)^3}{6h_j}+\frac{h_jx}{6}-\frac{h_jx_{j-1}}{6}-\frac{h_j^2}{6}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^3}{6h_j}-\frac{h_jx}{6}+\frac{h_jx_{j-1}}{6}\right]M_j\\ &+\frac{y_jx}{h_j}-\frac{xy_{j-1}}{h_j}+y_{j-1}-\frac{y_jx_{j-1}}{h_j}+\frac{y_{j-1}x_{j-1}}{h_j}\end{aligned}$$

and multiplying and dividing the single y_{j-1} term by h_j and substituting $h_j=x_j-x_{j-1}$ in the numerator gives:

$$=\left[\frac{(x_j-x)^3}{6h_j}+\frac{h_jx}{6}-\frac{h_jx_{j-1}}{6}-\frac{h_j^2}{6}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^3}{6h_j}-\frac{h_jx}{6}+\frac{h_jx_{j-1}}{6}\right]M_j$$
$$+\frac{y_jx}{h_j}-\frac{xy_{j-1}}{h_j}+\frac{x_jy_{j-1}}{h_j}-\frac{x_{j-1}y_{j-1}}{h_j}-\frac{y_jx_{j-1}}{h_j}+\frac{y_{j-1}x_{j-1}}{h_j}.$$

Making h_j a common denominator for all terms:

$$=\left[\frac{(x_j-x)^3+h_j^2x-h_j^2x_{j-1}-h_j^3}{6h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})^3-h_j^2x+h_j^2x_{j-1}}{6h_j}\right]M_j$$
$$\frac{+y_jx-xy_{j-1}+x_jy_{j-1}-x_{j-1}y_{j-1}-y_jx_{j-1}+y_{j-1}x_{j-1}}{h_j}$$

and expanding the cubed terms:

$$=\left[\frac{(x_j-x)^2(x_j-x)+h_j^2x-h_j^2x_{j-1}-(x_j-x_{j-1})h_j^2}{6h_j}\right]M_{j-1}+$$
$$\left[\frac{(x-x_{j-1})^2(x-x_{j-1})-h_j^2x+h_j^2x_{j-1}}{6h_j}\right]M_j+$$
$$\frac{y_jx-xy_{j-1}+x_jy_{j-1}-y_jx_{j-1}}{h_j}$$

$$=\left[\frac{(x_j-x)(x_j-x)^2}{6h_j}-\frac{(x_j-x)h_j^2}{6h_j}\right]M_{j-1}+\left[\frac{(x-x_{j-1})(x-x_{j-1})^2}{6h_j}-\frac{(x-x_{j-1})h_j^2}{6h_j}\right]M_j$$
$$+\frac{y_jx}{h_j}-\frac{xy_{j-1}}{h_j}+\frac{x_jy_{j-1}}{h_j}-\frac{y_jx_{j-1}}{h_j}$$

$$\text{So}\quad S(x)=\frac{(x_j-x)}{6h_j}\left[(x_j-x)^2-h_j^2\right]M_{j-1}+\frac{(x-x_{j-1})}{6h_j}\left[(x-x_{j-1})^2-h_j^2\right]M_j$$
$$+\frac{(x_j-x)y_{j-1}}{h_j}+\frac{(x-x_{j-1})y_j}{h_j}.$$

Appendix IV

W Matrix

0.2466	-0.105	0.0321	-0.0236	0.0623	-0.1689	0.9565
0.5617	-0.218	0.0633	-0.0352	0.0775	-0.2059	0.7566
0.8534	-0.2786	0.0784	-0.035	0.0615	-0.1584	0.4786
1.0301	-0.2261	0.0623	-0.0232	0.0304	-0.0739	0.2004
1	0	0	0	0	0	0
0.7177	0.4111	-0.1009	0.0293	-0.0164	0.0275	-0.0684
0.3225	0.8225	-0.1414	0.0394	-0.0163	0.0199	-0.0466
0	1	0	0	0	0	0
-0.1132	0.7916	0.3808	-0.0927	0.0269	-0.0128	0.0193
-0.0769	0.3726	0.8019	-0.1358	0.0376	-0.0133	0.0139
0	0	1	0	0	0	0
0.0313	-0.1332	0.7998	0.3784	-0.0912	0.0237	-0.00881
0.022	-0.0905	0.3782	0.8001	-0.1341	0.0334	-0.0091
0	0	0	1	0	0	0
-0.012	0.0373	-0.1356	0.8013	0.3748	-0.0818	0.0159
-0.0112	0.0267	-0.0924	0.3799	0.795	-0.1204	0.0225
0	0	0	0	1	0	0
0.0166	-0.016	0.0388	-0.1391	0.814	0.3407	-0.055
0.0228	-0.0161	0.0284	-0.0975	0.3987	0.7446	-0.0809
0	0	0	0	0	1	0
-0.0585	0.0287	-0.0204	0.0527	-0.1905	0.953	0.235
-0.1126	0.0524	-0.0273	0.0568	-0.1997	0.6807	0.5498
-0.1104	0.0499	-0.0206	0.0324	-0.1091	0.318	0.8397
0	0	0	0	0	0	1

Appendix V

Additional Econometric Topics

The first stage regression is essentially a time series routine to parameterize the load curve into a fixed number of coefficients. As is usually the case, time series regressions often lead to autocorrelated errors when estimated with the ordinary least squares estimator (Judge, et al., 1988). Although the estimates are unbiased, they no longer have the minimum variance among linear unbiased estimators, and hence, are not BLUE (Best Linear Unbiased Estimator). To correct for this problem, Poirier (1977) has investigated the use of a generalized least squares estimator as opposed to the ordinary least squares estimator in the first stage.

In his empirical work, which used 15 minute interval data for weekday residential consumption data, Poirier assumed that the length of the autoregressive process was eight periods (i.e., two hours). By regressing the ordinary least squares residuals on their lagged values, estimates of the autoregressive parameters were found for each residential customer and a transformation matrix constructed. The system was then transformed by multiplying the dependent and independent variables by this transformation matrix and the system re-estimated with ordinary least squares. If the assumption of eighth order autocorrelation is correct, this generalized least squares estimator will yield the best linear unbiased estimates.

In this analysis some experimentation with a generalized least squares estimator was performed. Following the conventions of Poirier, the first stage regressions were estimated under the assumption that the error term followed a second order autoregressive process (the order here is two since we are working with hourly data). This was done using the Statistical Analysis System (SAS) AUTOREG procedure, in which the autoregressive parameters are estimated using the Yule-Walker algorithm. Table V.1 presents results for the same farms in table 4.1, except that generalized least squares estimator is used as opposed to ordinary least squares estimator.

As can be seen, the estimates change little while some t-ratios increased and other t-ratios decreased. This is nothing out of the ordinary: generalized least squares essentially give unbiased estimates as does the ordinary least squares estimator, but with greater efficiency. Based on these results, there seems little to be gained by using a generalized least squares approach since little emphasis is placed on the significance of the first stage estimates; the fact that the estimates are unbiased is the most important factor. Furthermore, it is not clear that the auto-regressive

Table V.1 First stage regression results using generalized least squares.

Knots	Number of Cows 34	50	70	84	99
5:00am	0.776	1.611	1.603	5.429	8.106
	(1.4)	(2.5)	(1.2)	(2.5)	(7.2)
8:00am	4.825	6.121	7.812	20.136	17.306
	(7.2)	(8.1)	(4.9)	(7.6)	(12.7)
11:00am	5.861	3.443	11.936	9.807	5.577
	(8.2)	(4.3)	(7.0)	(3.4)	(3.8)
2:00pm	-0.036	2.559	-3.225	4.679	-0.748
	(-0.1)	(3.1)	(-1.9)	(1.6)	(-0.5)
5:00pm	1.675	4.918	8.739	11.169	14.041
	(2.4)	(6.3)	(5.3)	(4.1)	(10.0)
8:00pm	6.003	4.376	7.919	19.931	13.895
	(9.8)	(6.3)	(5.5)	(8.5)	(11.3)
12:00pm	1.850	2.901	0.551	2.195	-0.610
	(2.9)	(3.8)	(0.3)	(0.9)	(-0.4)
R^2	0.96	0.94	0.92	0.97	0.98
(t-ratios)					

structure is the same or even significant across all 25 sample farms. The implementation of combining results based on different auto-regressive structures in the same second stage regression are unclear. Finally, the second stage results for total electricity consumption, when the first stage is estimated using generalized least squares, are not terrible differnt from those based on first stage OLS results. Thus, the OLS estimates are used in the subsequent analysis. The second stage results when the first stage is estimated with GLS are reported in table V.2.

Table V.2 Second-stage regression coefficients for total electricity first stage estimated with GLS.

	Node						
	12:00am	5:00am	8:00am	11:00am	2:00pm	5:00pm	8:00pm
Intercept	175.029 (2.7)	-24.536 (-1.7)	52.499 (3.1)	6.950 (0.6)	58.764 (3.8)	-447.546 (-3.2)	-273.253 (-3.3)
Milk	4.55E-03 (7.8)	1.06E-03 (0.7)	1.76E-03 (1.1)	-1.55E-04 (-0.2)	4.29E-03 (3.3)	-4.72E-04 (-0.5)	-4.17E-03 (-6.9)
Square Milk	-9.66E-07 (-3.6)	2.52E-06 (4.2)	1.35E-07 (0.2)	3.54E-08 (0.1)	8.33E-07 (1.5)	3.04E-06 (5.6)	2.58E-06 (8.6)
Parlor	**	-2.732 (-9.3)	0.400 (1.2)	-2.054 (-11.8)	1.350 (6.0)	-0.593 (-1.9)	-0.339 (-2.1)
Bucket	**	-2.057 (-4.5)	1.671 (3.3)	-0.808 (-2.5)	-0.790 (-1.8)	-3.036 (-9.1)	-1.515 (-7.8)
Milk Cooler HP	**	**	0.019 (0.2)	0.037 (0.7)	-0.040 (-0.6)	0.252 (4.1)	0.014 (0.4)
Ice Bank	-0.440 (-1.2)	0.989 (1.7)	1.518 (2.5)	-0.776 (-2.0)	-1.440 (-2.6)	2.366 (4.6)	0.342 (1.1)
Ice Bank*Milk	-4.23E-04 (-0.6)	-2.06E-03 (-1.8)	1.66E-04 (0.1)	3.89E-03 (5.2)	3.71E-03 (3.5)	-2.74E-03 (-2.6)	3.65E-03 (6.0)
HT	**	-1.795 (-3.6)	0.854 (1.5)	-1.958 (-5.3)	**	-2.314 (-4.1)	-0.360 (-1.1)
HT*Milk	**	7.73E-04 (1.6)	-1.65E-03 (-2.9)	2.12E-03 (5.9)	**	1.04E-03 (1.9)	6.56E-04 (2.0)
Vacuum Pump HP	**	0.476 (7.8)	0.814 (12.7)	**	**	0.273 (4.1)	3.99E-03 (0.1)
Number of Fans	**	**	0.166 (2.2)	-0.064 (-1.3)	-0.228 (-3.4)	0.208 (3.3)	**
AM	**	9.802 (2.0)	-19.789 (-3.4)	-1.454 (-0.4)	-17.550 (-3.3)	**	**
Square AM	**	-0.852 (-2.1)	1.791 (3.7)	0.082 (0.3)	1.336 (3.0)	**	**
PM	-18.958 (-2.5)	**	**	**	**	49.772 (3.1)	30.490 (3.3)
Square PM	0.513 (2.4)	**	**	**	**	-1.375 (-3.1)	-0.843 (-3.2)
Spring	-2.13E-03 (-0.0)	-0.066 (-0.3)	-0.858 (-3.9)	-0.043 (-0.3)	-0.351 (-1.7)	-0.103 (-0.6)	-0.185 (-1.8)
Summer	-0.625 (-4.2)	-0.498 (-2.1)	-1.399 (-5.9)	-0.345 (-2.3)	-0.398 (-1.8)	-0.394 (-2.1)	-0.772 (-6.9)
Fall	-0.442 (-2.9)	-0.678 (-2.8)	-1.196 (-4.9)	-0.494 (-3.2)	-0.975 (-4.3)	-0.539 (-2.8)	-0.458 (-4.0)
N	469	469	469	469	469	469	469
R^2	.67	.86	.70	.44	.73	.89	.65
(t-ratios)							

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