Response to Time-of-Day Electricity Rates by Large Business Customers

Initial Analysis of Data from Ten U.S. Utilities

Rolla Edward Park, Jan Paul Acton
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Rolla Edward Park, Jan Paul Acton

September 1983

Prepared for the John A. Hartford Foundation and the Maryland Power Plant Siting Program
PREFACE

Commercial and industrial customers in the United States began to face time-of-day (TOD) electricity rates in the mid-1970s. By the early 1980s, more than 12,000 of these larger business customers faced TOD rates on an optional or a mandatory basis. Individual utilities have reported on effects in their service territories under TOD rates, but no study to date has analyzed data systematically across several utilities with TOD rates.

This report presents an analysis of original load data from ten utilities with a substantial variation in the terms of TOD prices and a broad mix of industries represented in the total data set. The detailed load data, along with price variations, permit the analysis of changes in patterns of consumption as a function of the prices that these customers face. The study should be of interest to utility ratemakers, regulators, interested parties in rate cases, and legislators who deal with energy policy. A related project for the Maryland Power Plant Siting Program will develop forecasting models for applying the results of this analysis.

The work was supported by grants from the John A. Hartford Foundation, the Maryland Power Plant Siting Program, and Rand corporate resources. It is part of Rand's extensive research on electricity demand and ratemaking.
ABSTRACT

This study reports an initial analysis of changes in relative peak electricity consumption for almost 4000 industrial and commercial customers in ten U.S. utilities with time-of-day (TOD) rates now in effect. Relative peak loads declined about one percentage point on average when TOD rates were introduced. A small fraction of customers reduced their peak loads substantially, but most customers (including commercial customers as a whole) have apparently not as yet changed their consumption patterns in response to TOD rates. Average change in load differs significantly by utility, industry, and year, and those changes are statistically related to the terms of the TOD rates that customers faced. Changes in load, while small in percentage terms, are large enough to justify TOD rates on a benefit/cost evaluation. Welfare gains average over $1000 per year per customer, against a metering cost of approximately $65 per year when new meters are needed to monitor TOD rates.
ACKNOWLEDGMENTS

This study would not have been possible without the generous cooperation and assistance of the ten U.S. utilities that provided primary data for the study. Individuals in the load forecasting and rate departments of Pacific Gas and Electric Company, Southern California Edison Company, the Los Angeles Department of Water and Power, Wisconsin Electric Power Company, Wisconsin Power and Light, Madison Gas and Electric, Commonwealth Edison, Consolidated Edison, Long Island Lighting Company, and Consumers Power Company all were generous with time and explanations that made it possible for us to acquire and develop the data set. In addition, a number of these individuals reviewed our analysis and provided helpful comments.

Joyce Davidson of Rand contributed importantly to the acquisition and understanding of the principal data files, and Karl Schwenkmeyer handled the extensive process of transforming a billion data elements into useful analytic files.

As part of our grant from the John A. Hartford Foundation, we received the assistance and guidance of an advisory committee consisting of Carol Barger, S. David Freeman, Carl Gilzow, Leigh Hammond, Barbara Haskew, William Pendleton, Grant Thompson, John Tillinghast, Dennis Whitney, and Charles Zielinsky—each of whom made useful comments at earlier stages of this research. In addition, Curt Biren and John Billings of the John A. Hartford Foundation were helpful throughout the process. Matthew Kahal of Exeter Associates, Suzanne Watkins of the Maryland Power Plant Siting Program, and our Rand colleagues Frank Camm, Bridger Mitchell, and Herman Quirmbach provided extensive comments which improved the draft considerably. We appreciate the assistance of each of these individuals.
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I. INTRODUCTION AND SUMMARY

Electricity ratemaking underwent a revolution during the 1970s along with most energy prices, but unlike prices for other forms of energy—where the primary impact was an abrupt increase in retail prices triggered by oil price increases in 1973 and 1979—electricity rates changed in form as well as level. During the 1970s, U.S. electric utilities discovered time-of-day (TOD) pricing¹ and began to apply it selectively to their customers.

Time-of-day rates have been in effect in Europe for several decades.² Although a few U.S. utilities have long offered offpeak waivers of their maximum demand charge—in some instances going back to the 1930s—the systematic differentiation of kw demand charges and kwh energy charges by time of day did not begin in U.S. utilities until the mid-1970s with almost simultaneous decisions in Wisconsin, California, and New York.³

In these three states—and in most others that have since introduced TOD rates—a similar pattern of rate change has occurred. The public utility commissions (PUCs) determined that cost of supply varied by time of day. They determined that TOD rates should be applied on a mandatory basis to the largest industrial and commercial customers; often these were a few hundred of the largest customers who already had complex metering equipment in place, permitting immediate application of TOD pricing structures. TOD rates were to be extended to other large and medium sized industrial and commercial customers as meters were made available and the initial application of TOD rates was observed. But because the benefits of applying TOD rates to residential customers were generally viewed as too uncertain on the

¹The terms “time-of-day pricing,” “peak load pricing,” “time-of-use pricing,” “seasonal pricing,” and “load management,” often used interchangeably, all reflect the fact that the cost of supplying electricity varies over time. Both the costs of capital and the operating costs vary with the amount of total electricity that is demanded, the cost of fuel inputs, the amount of hydraulic resources available, and the scheduled and unscheduled outages of generating equipment. The general term “time-of-use pricing” encompasses (1) rates that vary regularly by hour of the day (time-of-day rates), (2) rates that vary by season of the year (seasonal rates), and (3) rates that are invoked when costs of supply are unusually high (peak load or load management rates). Although some rate schedules analyzed in this report have seasonal features, we are chiefly interested in their effects on daily load patterns and thus generally use the term time-of-day (TOD) rates.

²See Mitchell, Manning, and Acton (1978) or Acton and McKay (1983).

³See Joskow (1979a) for a survey of U.S. ratemaking developments over this period.
basis of then available information, the commissions recognized the need for further study.

Several of the PUCs considered marginal costs of both fuel and capital in their review of rate structure. They often determined that marginal costs should be taken into account in determining rating periods for TOD rates (peak and offpeak hours and, in some cases, shoulder period hours and seasonal differentials) and that marginal costs should help determine the level of time differentiated kw and kwh charges. Without exception, however, the PUCs concluded that some elements of traditional ratemaking should be retained—most notably that the overall amount of revenue raised by a new rate structure should be constrained to levels based on total operating costs, historic accounting costs of capital, and allowed rate of return to the utility. This, however, did not mean that every customer was given a new rate structure that was expected to raise the same revenue as traditional rates. In their review of costs and rates, PUCs and the utilities often determined that some customers’ rates did not even cover the cost of the fuel used to generate their electricity; this was particularly true of the rates applied to some of the largest customers who had benefitted from volume discount rates during periods of declining capital costs and constant or declining fuel costs. With the turnaround in both fuel and capital costs over the course of the 1970s, many of these rates were no longer appropriate.⁴

The systematic review of TOD rates was given a legislative nudge by the Public Utilities Regulatory Policies Act (PURPA) standard of the National Energy Act of 1978. It required that each of the state public utilities commissions review eleven ratemaking standards—including seasonal, TOD, lifeline, and volume discount rates—although it did not obligate states to adopt any particular rate structure.⁵ By the end of the 1970s several thousand of the largest industrial and commercial customers faced TOD rates on a mandatory basis, and a large number had TOD rates available as an option.

⁴This is not the place for a detailed review of long-term trends of operating and capital costs in electricity generation. Fuel costs rose sharply during the 1970s, led by the four-fold increase in oil prices in 1973/74. Capital costs, the investment per kw of generating capacity, fell for several decades in real terms due to technological advances and economies of scale, but most analysts agree that the downward trend in costs ended in the late 1960s and costs are now constant or rising in real terms.

⁵See Joakow (1979b) for a review of the PURPA standards and their application to electricity ratemaking.
PURPOSE OF THE STUDY

This report analyzes the effects of introducing TOD rates on patterns of electricity use for a significant sample of these large industrial and commercial customers. There are several reasons for wanting to perform this analysis.

1. Many utilities are considering introducing TOD rates for the first time and want to know what to expect in terms of the effects on kilowatt-hour consumption, the time pattern of use, and revenue, and how much variability to expect among important subgroups of customers.

2. Many utilities that have already introduced TOD rates for their largest customers are considering extending the rates to additional medium sized customers; they also want to know the likely effects of doing so.

3. Some utilities presently offer TOD rates on an optional basis and are considering making these rates mandatory; they want to know the consequences of doing so.

4. The design of TOD rates presents several opportunities for varying the number of ratemaking periods, the length of rating periods, the relative emphasis on kw and kwh components of the rates, and so forth; evidence about the experience with these different components of rates will assist ratemakers in their analysis.

5. If there are important differences among individual customers in their response to TOD rates, both utilities and customers may want to better understand the types of differences—and perhaps some of the reasons for them—in order to help customers deal with TOD rates that they may face.

6. If TOD rates have produced undesirable effects, it may be important to review them for significant modification or cancellation; systematic evaluation can assist in that determination as well.

DATA AND METHODOLOGY FOR THE STUDY

The data for this study are taken from ten U.S. utilities that now have mandatory TOD rates in effect for their largest commercial and industrial customers. The utilities are found in five different states and represent a cross-section of customer characteristics as well as economic and climatic features. Because TOD rates vary substantially
in their price levels and structural features from utility to utility we can estimate the independent effects of various features of the tariffs, such as energy (kwh) charges versus demand (kw) charges. Such estimates would not be possible if, as in other studies, we had data from only a single utility.

The ten-utility data base contains some of the earliest U.S. experience with TOD rates. By the end of 1980, the rates applied to over 6000 customers. As best we can determine, this accounts for the majority of firms on mandatory TOD rates at that time.

Although some U.S. utilities have offered optional TOD rates to their largest customers, in each of the utilities we studied the rates are mandatory to all customers in the service class. Each utility began by applying the TOD rates to their very largest customers—defined either by total energy consumed, the maximum rate of consumption, or by the voltage level of service. In each utility, the same rates were applied to commercial and industrial customers at a given size designation. Initially, the rates often applied to only a small number of the largest business customers, generally 100 to 200 customers, but although they amounted to only 1 or 2 percent of the number of commercial and industrial customers, they accounted for 20 to 30 percent of all electricity used by commercial and industrial customers in these utilities. Since their first introduction in the mid to late 1970s, the TOD rates have been extended to additional commercial and industrial customers on a mandatory basis by all ten utilities, starting with the next group of customers designated by size.

In our analysis we look at each individual firm's pattern of use before and after TOD rates and then combine the data from all ten utilities to determine the overall statistical profile of use during peak and offpeak periods. By combining these data across utilities we can determine the quantitative effects of different components of the rate structure and other factors that influence patterns of use—something that cannot be done with data from a single utility alone. Because ours is the first study to combine data across utilities, we took a deliberately exploratory approach to the data. We examine patterns of use with relatively general statistical models which impose a minimum of structure and assumptions on the data; we let the data "speak for themselves." Once the basic character of response is understood in this initial analysis, we believe that future analysis can proceed on a firmer footing to apply greater structure in modeling.
SUMMARY OF RESULTS

In subsequent sections, we examine patterns of use by individual customers before TOD rates and compare them with patterns after TOD rates are in effect. We analyze the effect of a number of factors that might influence response, including features of the rate structure, the customer's industrial classification, weather, and location. Details of the data, methodology, and analysis follow in later sections, but an overview of the results is given here.

- Business firms as a group respond to TOD rates by reducing relative consumption in peak pricing periods and increasing relative consumption in offpeak periods. The magnitude of change is small—about 1 percent reduction in relative peak load—but because of its high statistical significance, there is virtually no chance that the reduction is due to random fluctuations.
- Industrial customers as a group reduce their relative peak loads somewhat more than the overall average of 1 percent for all businesses. Commercial customers as a group have not yet responded to TOD rates in any measurable way.
- Some industrial classifications respond a lot more than others—notably wood products, primary metals, and machinery manufacturing. The average response in these industries ranges from 5 to 9 percent reduction in relative peak load.
- Firms differ in their responsiveness, and most firms do not appear to respond at all. Firms that do respond do so energetically. About 4 percent of all industrial customers respond; on average, these firms reduce their relative peak loads by about 35 percentage points.
- Price plays a major role in response. Higher peak prices are significantly associated with larger reductions in peak load. This reduction occurs whichever sort of TOD charge is in effect—either a peak energy charge or a peak demand charge.
- Larger customers respond more. This relationship between size and response is apparent after adjusting for prices, weather, region of the country, and industrial classification.
- Weather has the expected effect—extremely hot or extremely cold weather decreases the response to TOD rates.

---

"Relative peak consumption" or "relative peak load" is the ratio of average hourly energy use during peak periods to average hourly use over a 24-hour weekday period. This measure focuses on the daily pattern of demand and averages out the factors that shift overall usage.
IMPLICATIONS FOR POLICY

When regulators consider introducing TOD rates, their evaluation includes two important elements: the fairness of the TOD rate compared with existing rate structures and the efficiency gains (or benefits versus cost) associated with introducing the new rate. In those cases when TOD rates were introduced on a mandatory basis, the PUCs apparently found that the improvement in fairness was sufficient grounds for introducing the rate—at least for the very largest customers. As costs of supply vary by time of day, a TOD rate structure produces bills to individual customers that more accurately reflect costs; thus the PUCs deemed it to be fairer. This focus on fairness alone for these very large customers may have been reinforced by the fact that suitable metering was often already in place, so the incremental costs of a TOD rate were essentially zero.

In a consideration of efficiency, the incremental costs associated with metering a more complicated TOD rate structure must be taken into account. The benefits—in terms of lower operating and capital cost to the electric utility as well as the improvement in the dollar value of customer well-being—need to exceed the incremental cost of TOD metering to pass the efficiency standard. Although PUCs often did not demand evidence that benefits exceed costs when introducing rates for the very largest customers, they often ask for such evidence before extending TOD rates on a mandatory basis to additional customers whose relative metering costs may be more important.

We concentrate our analysis on the efficiency gains associated with introducing TOD rates using data at hand. Again, the details of our analysis are provided in the following sections, but the principal policy implications are summarized here.

1. **Overall, the benefits of introducing TOD rates for large customers exceed the incremental costs.** On average, the sum of gains to the utilities and the customers was about $1000 per customer per year. When new meters are needed for TOD rates, suitable units are available at a cost between $300 and $600—depending on the complexity of the rate structure—with a corresponding annual carrying charge of $35 to $70. Therefore, the metering costs could be recovered in less than one year given the observed responsiveness, and the TOD rates yield a net benefit of over $900 per customer annually.

2. **Although slightly higher net benefits could be obtained in the short run by applying TOD rates only to responsive industrial customers, the resulting savings in metering costs would be small compared to the probable long-run gains from wider application.** TOD rates for large business customers that are unresponsive in the short run will encourage
long-run adjustments such as the installation of computerized load management systems. Even a small additional long-run response would repay the costs of metering all large customers, and more widespread long-run response would yield very large net benefits.

3. **Extension of TOD rates to smaller business customers will yield additional efficiency gains.** Our calculations suggest that even the observed short-run response justifies applying TOD rates to business customers with average loads down to 30 kwh per hour. In the long run, the cutoff point will probably be even lower.

**OVERVIEW OF THE REPORT**

This report represents an analysis of response to TOD rates, starting with an overview of the aggregate average response and moving into an increasingly fine breakdown by customer groupings and features of the rate structure. We then evaluate TOD rates by formal welfare economic standards.

Section II describes the data from ten utilities and the subset of data used for the principal analysis.

Section III describes the distribution of changes in relative peak load in response to TOD rates. It presents mean response by industry and by utility, and distinguishes responsive from unresponsive firms.

Section IV specifies and estimates a nonlinear regression model that relates response to prices, industry, and other factors.

Section V presents a formal welfare analysis of the significance of TOD rates for this set of larger U.S. industrial and commercial customers.

Finally, Sec. VI compares our results with the results of previous studies and provides suggestions for future research topics.
II. THE TEN-UTILITY DATABASE

This study uses an extensive set of data on individual customer electricity consumption for the large industrial and commercial customers of ten utilities located throughout the United States. This section describes how we processed the load data and combined them with information on prices and other variables to create the data files for analysis.

LOAD DATA

The ten utilities listed in Table 2.1 supplied us with load data for their large customers currently on mandatory time-of-day rates. The original data are very detailed; at a minimum, they include hour-by-hour energy (kwh) consumption for each customer, and most of the utilities supplied half-hourly or 15-minute data. Thus we have up to $4 \times 24 \times 365 = 35,040$ consumption figures per customer per year in the raw data files.

Table 2.1

<table>
<thead>
<tr>
<th>Utility</th>
<th>Customers</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>California:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCE  Southern California Edison</td>
<td>575</td>
<td>5</td>
</tr>
<tr>
<td>DWP  Los Angeles Department of Water and Power</td>
<td>262</td>
<td>5</td>
</tr>
<tr>
<td>PGE  Pacific Gas and Electric</td>
<td>1382</td>
<td>6</td>
</tr>
<tr>
<td>Midwest:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WEP  Wisconsin Electric Power Company</td>
<td>588</td>
<td>4</td>
</tr>
<tr>
<td>MGE  Madison Gas and Electric</td>
<td>32</td>
<td>4</td>
</tr>
<tr>
<td>WPL  Wisconsin Power and Light</td>
<td>407</td>
<td>4 1/2</td>
</tr>
<tr>
<td>CMN  Commonwealth Edison</td>
<td>540</td>
<td>2</td>
</tr>
<tr>
<td>COP  Consumers Power Company</td>
<td>2065</td>
<td>4</td>
</tr>
<tr>
<td>New York:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LIL  Long Island Lighting Company</td>
<td>429</td>
<td>5</td>
</tr>
<tr>
<td>CON  Consolidated Edison</td>
<td>65</td>
<td>2 1/2</td>
</tr>
<tr>
<td>Total:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6345</td>
<td></td>
</tr>
</tbody>
</table>

NOTE: Customer counts are after exclusion of accounts with no SIC code information. All data extend through 1980. There are no data on loads before T0D rates were introduced for CMN and COP.
The utilities also supplied us with some other information about each customer. Two pieces of information are particularly important in our analysis: the Standard Industrial Classification (SIC) code allows us to analyze separately groups of customers that are engaged in similar businesses. SIC codes are available at the four-digit level of detail from most of the utilities, and at least the two-digit level for all ten of them. We use the two-digit level in this report. Second, tariff or customer classification codes, together with information about which customers received high-voltage discounts, allowed us to calculate the prices facing each customer each month.

On the other hand, we do not have any information about such details of each customer's operation as output levels, number of shifts worked, or particular processes used. Our agreement with the utilities supplying data generally precluded us from contacting individual customers for additional information not already in the utilities' files.

Table 2.1 shows for each utility the approximate number of customers in the raw files and the number of years the data cover. The number of customers is much higher for some utilities than for others. The data span periods ranging from two years to over five years, depending on the utility. Data for eight of the ten utilities include, for some or all of their customers, loads both before and after TOD rates were introduced.

We processed the immense amount of raw data into smaller summary files suitable for analysis in several steps. First, we calculated certain average kwh consumption figures for each customer. The averages were taken over month-long periods during which prices were constant or nearly constant. For most of the utilities, these periods were billing months, that is, the period from one meter reading to the next. The average consumption figures that we use in this analysis are those for peak, shoulder, and offpeak periods on weekdays. "Weekdays" exclude Saturdays, Sundays, and a standard list of seven holidays.  

Second, we calculated the prices that faced each customer each month and merged them with the consumption files. Third, we merged in additional weather and economic data from various sources. Weather data include heating and cooling degree days. Economic data

---

1 We exclude weekends in order to get average consumption measures that do not depend on the number of weekend days in a particular month. Offpeak and shoulder consumption on weekends typically differs from offpeak and shoulder consumption on weekdays. Thus consumption measures that lump together weekdays and weekends will fluctuate from year to year with the calendar even when underlying consumption patterns are constant. A somewhat more complicated alternative to exclusion of weekends would be to include them, but to calculate consumption figures adjusted to a standard number of weekend days each month.
include price indexes, wage rates, and hours worked, by industry and state. The weather variables and price indexes are used in the regression analysis in Sec. IV. The other economic variables were used in preliminary analyses. We did not find them useful, possibly because incomplete coverage resulted in serious missing data problems.

Fourth, we excluded observations for (1) customers with no SIC code available, (2) customers on a few infrequently used special tariffs, (3) observations for a particular customer during a particular month if his consumption fell below an arbitrary low cutoff level (100 kwh per hour averaged over the full month), (4) observations for unusual consumption patterns that resulted in a zero marginal price (for example, consumption below a minimum level, so that only a monthly "customer charge" was effective), and (5) observations with more than 24 missing hours of consumption data during the month on the raw data file.

Fifth, we selected observations for one summer month (June) and one winter month (November) each year. These months were chosen to avoid, to the extent possible, times when prices were changing for a lot of customers—for example, months during which rates are changing from summer to winter schedules, or months during which time-of-day tariffs are introduced for the first time. A priori, these may not seem to be typical summer and winter months. However, initial analysis of two alternate months—February and August—suggests that June and November are not atypical. Appendix Tables A.1, A.2, and A.3 compare February and August average response with the June and November response that we analyze here.

We analyze changes in relative peak load, calculated by taking first differences separately for summer and winter months. For example, the summer 1977 change in relative peak load is June 1977 relative peak load minus June 1976 relative peak load. Thus the "change" file that we analyze includes each year observations only for customers observed both that year and the year before. Failure to link up year-to-year dropped some more observations. The number of remaining observations are shown in Table 2.2.

In the table we distinguish among three types of observations: those for which standard rates were in effect during both the initial and the final year, those during which TOD rates were first introduced, and those for which TOD rates continued in effect. For example, most SCE A81 customers were on standard rates until October 1977 and on TOD rates after that. Thus the summer 1977 observations for these customers (June 1977 relative peak load minus June 1976 relative peak load) are for continuing standard rates, the winter 1977 and summer
Table 2.2
NUMBER OF OBSERVATIONS IN CHANGE FILE

<table>
<thead>
<tr>
<th>Month</th>
<th>Continuing Standard Rates</th>
<th>New TOD Rates</th>
<th>Continuing TOD Rates</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>June 1977</td>
<td>199</td>
<td>194</td>
<td>0</td>
<td>393</td>
</tr>
<tr>
<td>November 1977</td>
<td>185</td>
<td>186</td>
<td>0</td>
<td>371</td>
</tr>
<tr>
<td>June 1978</td>
<td>774</td>
<td>331</td>
<td>1293</td>
<td>2398</td>
</tr>
<tr>
<td>November 1978</td>
<td>1055</td>
<td>274</td>
<td>1233</td>
<td>2562</td>
</tr>
<tr>
<td>June 1979</td>
<td>1088</td>
<td>312</td>
<td>1735</td>
<td>3135</td>
</tr>
<tr>
<td>November 1979</td>
<td>732</td>
<td>652</td>
<td>1616</td>
<td>3000</td>
</tr>
<tr>
<td>June 1980</td>
<td>434</td>
<td>885</td>
<td>2556</td>
<td>3875</td>
</tr>
<tr>
<td>November 1980</td>
<td>444</td>
<td>462</td>
<td>2895</td>
<td>3801</td>
</tr>
<tr>
<td>Total</td>
<td>4911</td>
<td>3296</td>
<td>11328</td>
<td>19535</td>
</tr>
</tbody>
</table>

1978 observations are for introduction of TOD rates, and the winter 1978 through winter 1980 observations are for continuing TOD rates.

There are nearly 20,000 total observations on year-to-year changes in relative peak load, and over 3,000 for changes when TOD rates were introduced.

PRICE DATA

We calculated prices for each customer each month based on the utilities' rate sheets. We took into account applicable fuel cost adjustments and any discounts (such as high-voltage discounts) that applied to each customer.

Time-of-day rates were introduced at different times by the different utilities in our data base. Three utilities (SCE, PGE, and WPL) have themselves introduced time-of-day rates at different times for different groups of customers (starting with the largest consumers and later adding those with smaller maximum demand levels). Table 2.3 shows when the rates were introduced, distinguishing among customer classes where relevant.

When we say that time-of-day rates were introduced at the times indicated in Table 2.3, we are focusing on only one aspect of what may be fairly complex rate structures, namely on time-of-day energy (kwh) price differentials. Prior to the dates in Table 2.3, each customer paid the same price per kwh around the clock; after those dates, they paid a
Table 2.3
DATES WHEN TIME-OF-DAY ENERGY RATES WERE INTRODUCED

<table>
<thead>
<tr>
<th>Utility/Classification</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCE/A81</td>
<td>October 1977</td>
</tr>
<tr>
<td>SCE/T73</td>
<td>July 1979</td>
</tr>
<tr>
<td>DWP</td>
<td>December 1978</td>
</tr>
<tr>
<td>PGE/A23</td>
<td>February 1977</td>
</tr>
<tr>
<td>PGE/A22</td>
<td>December 1979</td>
</tr>
<tr>
<td>PGE/A21</td>
<td>March 1981</td>
</tr>
<tr>
<td>WEP</td>
<td>January 1978</td>
</tr>
<tr>
<td>MGE</td>
<td>February 1979</td>
</tr>
<tr>
<td>WPL/CP1</td>
<td>January 1977</td>
</tr>
<tr>
<td>WPL/CP4</td>
<td>December 1978</td>
</tr>
<tr>
<td>CMN</td>
<td>December 1978</td>
</tr>
<tr>
<td>COP</td>
<td>April 1976</td>
</tr>
<tr>
<td>LIL</td>
<td>February 1977</td>
</tr>
<tr>
<td>CON</td>
<td>January 1980</td>
</tr>
</tbody>
</table>

higher price per kwh during specified peak periods and a reduced price during offpeak and (sometimes) shoulder hours.

For some of the utilities, maximum demand (kw) charges had time-of-day features even before the dates set out in Table 2.3. As shown in Table 2.4, PGE, WEP, and WPL all offered some sort of offpeak demand waiver prior to those dates. The offpeak demand waiver converts what is formally a noncoincident demand charge (that is, a charge for the maximum kw demanded anytime during the billing month) into what is in practical effect a peak-period demand charge (that is, a charge for the maximum kw demanded during peak hours of the billing month).

After the dates in Table 2.3, all utilities charged higher energy prices during peak periods than during offpeak periods. Most also levied demand charges that applied during peak (and maybe shoulder) periods only. A few continued to collect for noncoincident demand.
Table 2.4
AVERAGE PRICES BEFORE INTRODUCTION OF TOD RATES

<table>
<thead>
<tr>
<th>Utility</th>
<th>Date</th>
<th>Energy price (cents/kwh)</th>
<th>Demand price (dollars/kw)</th>
<th>P</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCE/A81</td>
<td>June 1977</td>
<td>2.11</td>
<td></td>
<td>--</td>
<td>0.78</td>
</tr>
<tr>
<td>DWP</td>
<td>Nov. 1978</td>
<td>2.20</td>
<td></td>
<td>--</td>
<td>0.25</td>
</tr>
<tr>
<td>PGE/A23</td>
<td>Nov. 1976</td>
<td>1.80</td>
<td>1.75</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>WEP</td>
<td>Nov. 1977</td>
<td>1.80</td>
<td>2.66</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>MGE</td>
<td>Nov. 1978</td>
<td>2.65</td>
<td>--</td>
<td>3.33</td>
<td></td>
</tr>
<tr>
<td>WPL/CP4</td>
<td>Nov. 1978</td>
<td>1.62</td>
<td>4.44</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>LIL</td>
<td>Nov. 1976</td>
<td>2.91</td>
<td>--</td>
<td>3.30</td>
<td></td>
</tr>
<tr>
<td>CON</td>
<td>Nov. 1979</td>
<td>4.66</td>
<td>--</td>
<td>10.02</td>
<td></td>
</tr>
</tbody>
</table>

NOTE: P = peak (noncoincident demand charge with offpeak waiver); N = noncoincident demand charge without offpeak waiver. Prices shown are for the last month in the data file prior to introduction of TOD rates.

There is quite a range of values for the three main components of a time-of-day tariff (time-of-day energy prices, time-of-day demand prices, and noncoincident demand prices) represented among the ten utilities in our data base. Table 2.5 illustrates this range using average prices during June 1980, when time-of-day rates were in effect for all ten utilities. Energy price differentials range from very small (for example, 0.3 cent/kwh in SCE) to quite substantial (3.4 cents/kwh in DWP). Time-of-day differentials for demand charges range from zero (in DWP) to very substantial amounts (for example, $17/kw per month in CON).

In some cases, demand (kw) charges are subject to so-called "ratchet" provisions. A ratchet provides that the demand charge shall be based on either maximum demand during the current month, or some percentage of the maximum demand during a number of (typically 12) preceding months, whichever is higher. With a ratchet in effect, there is no marginal charge for sufficiently low levels of maximum demand. Among our utilities, three apply ratchets to peak-period demand charges; the percentages are 75, 60, and 25. These peak-period demand ratchets will be effective only in extreme
Table 2.5
AVERAGE TOD PRICES
(June 1980)

<table>
<thead>
<tr>
<th>Utility</th>
<th>Energy price (cents/kwh)</th>
<th>Demand price (dollars/kw)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P</td>
<td>S</td>
</tr>
<tr>
<td>SCE/A81</td>
<td>5.17</td>
<td>5.02</td>
</tr>
<tr>
<td>DWP</td>
<td>7.98</td>
<td>--</td>
</tr>
<tr>
<td>PGE/A23</td>
<td>5.16</td>
<td>4.96</td>
</tr>
<tr>
<td>WEP</td>
<td>3.24</td>
<td>--</td>
</tr>
<tr>
<td>MGE</td>
<td>3.40</td>
<td>--</td>
</tr>
<tr>
<td>WPL/CP4</td>
<td>2.91</td>
<td>--</td>
</tr>
<tr>
<td>CKN</td>
<td>3.46</td>
<td>--</td>
</tr>
<tr>
<td>CPD</td>
<td>3.01</td>
<td>2.71</td>
</tr>
<tr>
<td>LIL</td>
<td>5.56</td>
<td>4.93</td>
</tr>
<tr>
<td>CON</td>
<td>4.90</td>
<td>--</td>
</tr>
</tbody>
</table>

NOTE: P = peak, S = shoulder, O = offpeak, N = noncoincident.

circumstances, so we choose to ignore them. We also ignore noncoincident demand ratchets in four utilities, although these range up to 100 percent, and thus will frequently be effective. Binding ratchets may be one reason that we find (in Sec. IV) that noncoincident demand charges have a relatively small effect on relative peak loads.

Different tariffs also have different peak period definitions. These are shown in Table 2.6. Again, there are substantial differences from utility to utility. The length of the peak period ranges from four hours (PGE, winter) to 17 hours (LIL, winter).

RATE GROUPS AND INDUSTRIES REPRESENTED

Finally, we show the number of customers classified in two different ways in Table 2.7. The counts of customers by SIC code and by utility/customer class are for June 1980. We counted separately all two-digit industrial SIC codes for which we had a substantial number of observations; the remaining industrial customers are included in the category labeled "industrial nec," for "industrial customers not elsewhere classified." In preliminary work, we did the same thing for commercial customers, distinguishing among hospitals, retail stores, etc. We found, however, that commercial response was small, insignificant, and not much different for different SIC codes. Consequently, we report all commercial customers in a single group.
Table 2.6
PEAK-PERIOD DEFINITIONS
(Weekdays, local time)

<table>
<thead>
<tr>
<th>Utility</th>
<th>Summer</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCE</td>
<td>P: 1300-1900</td>
<td>1700-2200</td>
</tr>
<tr>
<td></td>
<td>S: 0900-1300, 1900-2300</td>
<td>0800-1700</td>
</tr>
<tr>
<td>DWP</td>
<td>P: 1200-2000</td>
<td>1100-1900</td>
</tr>
<tr>
<td>PGE</td>
<td>P: 1230-1830</td>
<td>1630-2030</td>
</tr>
<tr>
<td></td>
<td>S: 0830-1230, 1830-2230</td>
<td>0830-1630, 2030-2230</td>
</tr>
<tr>
<td>WEP</td>
<td>P: 0900-2100</td>
<td>0800-2000</td>
</tr>
<tr>
<td>MGE</td>
<td>P: 1000-2100</td>
<td>1000-2100</td>
</tr>
<tr>
<td>WPL</td>
<td>P: 0800-2200</td>
<td>0800-2200</td>
</tr>
<tr>
<td>CMN</td>
<td>P: 0900-2200</td>
<td>0900-2200</td>
</tr>
<tr>
<td>COP</td>
<td>P: 1000-1700</td>
<td>1700-2100</td>
</tr>
<tr>
<td></td>
<td>S: 1700-2100</td>
<td>1000-1700</td>
</tr>
<tr>
<td>LIL</td>
<td>P: 1000-2200</td>
<td>0700-2400</td>
</tr>
<tr>
<td></td>
<td>S: 0700-1000, 2200-2400</td>
<td>--</td>
</tr>
<tr>
<td>CON</td>
<td>P: 0800-2200</td>
<td>0800-2200</td>
</tr>
</tbody>
</table>

NOTE: P = peak; S = shoulder

In the case of some utilities, their very largest customers were placed on TOD rates on or before the first monthly observation provided to us. As a consequence, these very largest customers cannot be observed in the before/after analysis of TOD rates. They are only observed as continuing on TOD rates. We are unable to determine the effect of this limitation on the overall results, but discussions with some utility analysts suggested that some of these customers made significantly above-average response when TOD rates were introduced.

Industrial groupings must always be interpreted with a degree of caution due to intrinsic imprecision in the classification process. First, the SIC codes designate the primary activity of the firm; for multiproduct firms, this will involve some imprecision of assignment. Second, our analysis distinguishes industrial firms at the two-digit level, as is often done in industrial studies. In some cases, this involves a set of fairly homogeneous producers, but in others the firms' outputs are quite diverse. In future analysis, it may be useful to analyze a subset of firms at the four-digit level where products are more homogeneous.
Table 2.7
CUSTOMER COUNTS BY INDUSTRY AND BY UTILITY
(June 1980)

<table>
<thead>
<tr>
<th>By Industry:</th>
<th>By Utility/Customer Class:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrial nec</td>
<td>SCE/A81 88</td>
</tr>
<tr>
<td>20 Food products</td>
<td>SCE/T73 438</td>
</tr>
<tr>
<td>24 Wood products</td>
<td>DWP 159</td>
</tr>
<tr>
<td>26 Pulp and paper</td>
<td>PGE/A23 65</td>
</tr>
<tr>
<td>28 Chemicals</td>
<td>PGE/A22 395</td>
</tr>
<tr>
<td>29 Petroleum</td>
<td></td>
</tr>
<tr>
<td>30 Rubber and plastic</td>
<td>PGE/A21 434</td>
</tr>
<tr>
<td>32 Stone, clay, glass</td>
<td>WEP 335</td>
</tr>
<tr>
<td>33 Primary metals</td>
<td>MGE 16</td>
</tr>
<tr>
<td>34 Fabricated metals</td>
<td>WPL/CP1 125</td>
</tr>
<tr>
<td>35 Machinery</td>
<td>WPL/CP4 89</td>
</tr>
<tr>
<td>36 Electrical machinery</td>
<td>CMN 485</td>
</tr>
<tr>
<td>37 Transportation equip</td>
<td>COP 1020</td>
</tr>
<tr>
<td>48 Communications</td>
<td></td>
</tr>
<tr>
<td>49 Utilities</td>
<td>LIL 175</td>
</tr>
<tr>
<td>Total industrial</td>
<td>CON 51</td>
</tr>
<tr>
<td>Total commercial</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>Total 3875</td>
</tr>
</tbody>
</table>

Third, the classifications are those contained in the utility data files; in some cases they were supplied by the customers, and in some cases they were assigned by the utility and they vary in their accuracy.

All in all, there are enough customers in different industries and sufficient variation in the characteristics of the various utilities' tariffs (prices, peak-period definitions) to hold out hope of identifying the separate effects of the different characteristics on load curves.
III. MEANS AND DISTRIBUTIONS OF RESPONSE TO TOD RATES

In this section, we first define our measure of response and discuss its advantages and disadvantages. Second, we present tables of average response for customers classified in various ways. Third, we look at the distributions of response by individual customers, and use the distributions to distinguish between “responsive” and “unresponsive” customers.

DEFINITION OF RESPONSE: CHANGE IN RELATIVE PEAK LOAD

We shall measure customers’ response to TOD rates by changes in their relative peak loads—the ratio of their average energy consumption during peak hours to their average weekday consumption around the clock. We expect that TOD rates tend to flatten load curves and hence to reduce relative peak load.

The concept of relative peak load is illustrated in Fig. 3.1, which shows the average weekday load curve for a particular hypothetical customer during a particular month. The horizontal line A shows this customer’s average load over the full 24-hour period; the horizontal line B is his average load during just the peak period. Relative peak load for this customer is the ratio of the height of B to the height of A. Relative peak load can be expressed either as a decimal fraction or as a percent. In Fig. 3.1, average load during peak hours is about 60 percent higher than 24-hour average consumption. Thus relative peak load is equal to 1.6, or 160 percent.

Change in relative peak load is simply the difference between relative peak load during a particular month this year and relative peak load during the same month last year. If Fig. 3.1 represents this year, and the same customer last year had a relative peak load of 170 percent, then the change in relative peak load is \(160 - 170 = -10\) percentage points. Note that by this definition, both increases and decreases in relative peak load of more than 100 percentage points are possible.\(^1\)

\(^{1}\)Relative peak load is closely related to another commonly used measure of peakiness: the peak period share of total energy consumption. If we denote relative peak load by \(r\) and peak period share by \(s\), then \(r = s \cdot \frac{h(p)}{h(o)}\), where \(h(p)\) and \(h(o)\) are the number of peak and offpeak hours, respectively. The multiplier \(\frac{h(p)}{h(o)}\) is a
Fig. 3.1—Relative peak hourly consumption

A complete characterization of response would involve several other measures in addition to change in relative peak load. These additional measures include (1) change in total energy consumption; (2) change in relative load during shoulder periods, or even better, change in relative load hour by hour throughout the day; (3) change in weekend loads; (4) change in maximum demand or load factor; (5) change in load at the time of the system peak. Our future work may analyze one or more of these additional measures.

We choose to focus our initial analysis on changes in relative peak load for several reasons:

- We expect that the largest effect of TOD prices is on the daily pattern of electricity consumption, not on total energy consumption; we may not be able to explain variations in overall level of consumption without more detailed information on
individual customer characteristics than we now have. Using relative load rather than absolute load or total consumption abstracts from the problem of scale of operation for any individual customer.

- Shoulder prices, when present at all, are very close to offpeak prices for most of the customers in our sample; thus we expect little difference between changes in relative load during shoulder periods and changes during offpeak periods.

- We excluded weekends from our analysis for the reason already discussed in Sec. II.

- Maximum kw demand for individual customers is perhaps of less interest than their peak period energy consumption. Individual customers' maximum demands occur at different times and on different days; knowledge of changes in maximum demand levels would tell us little or nothing about changes in system peak loads.

- Loads at system peak are calculated from a single hourly (or 15-minute) observation per customer, and hence are subject to substantially more random variation than are the broader averages that we analyze here. We choose to analyze the more tractable variable first, in the expectation that changes in load during peak periods are closely related to changes at the system peak for large customers with high load factors, at least for the types of tariffs in our sample.\(^2\)

- Finally, using changes in relative load as the measure of response lets each customer serve as his own "control" and helps account for any missing explanatory variables or persistent individual customer effects.

Although change in relative peak load has important advantages as a measure of response to TOD prices, it also has a potentially serious disadvantage: If total consumption changes significantly across customers from one year to the next, then the average of individual customer changes in relative peak load is not in general equal to the change in relative peak load for all customers together.\(^3\) A simple example in Table 3.1 illustrates this aggregation problem.

The table shows a hypothetical situation in which both Customer A and Customer B reduce relative peak load by 10 percentage points, but aggregate relative peak load declines by less than 9 percentage points.

\(^2\)Tariffs that allow load interruption at the utilities option, or that levy a demand charge that applies only at system peak, are another matter.

\(^3\)We are grateful to Herman Quirmbach for emphasizing this point in his review.
Table 3.1  
ILLUSTRATION OF AGGREGATION PROBLEM  
FOR RELATIVE PEAK LOAD (RPL)

<table>
<thead>
<tr>
<th></th>
<th>Standard Rates</th>
<th></th>
<th>TOD Rates</th>
<th></th>
<th>Change in RPL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peak kwh</td>
<td>Daily kwh</td>
<td>RPL</td>
<td>Peak kwh</td>
<td>Daily kwh</td>
</tr>
<tr>
<td>Customer A</td>
<td>132</td>
<td>110</td>
<td>120.0</td>
<td>110</td>
<td>100</td>
</tr>
<tr>
<td>Customer B</td>
<td>150</td>
<td>100</td>
<td>150.0</td>
<td>147</td>
<td>105</td>
</tr>
<tr>
<td>Total</td>
<td>282</td>
<td>210</td>
<td>134.3</td>
<td>257</td>
<td>205</td>
</tr>
</tbody>
</table>

In general, the weighted average of individual customer’s changes in relative peak load (calculated using initial-year average daily consumption as weights, as we always do in this report) will equal aggregate change in relative peak load only when initial-year and final-year average daily consumptions have the same relative size for all customers in both years. (For example, this would be true in the hypothetical situation described in the table if daily average consumption under TOD rates were 110 for Customer A and 100 for Customer B. It would also be true if daily average consumption under TOD rates were 55 for Customer A and 50 for Customer B.)

Fortunately, the relative size of average daily consumption for our sample of customers is apparently similar enough from year to year so that our measure does not have serious aggregation problems. The weighted average of individual customer response is usually almost the same as the response for all customers as a group. Appendix Tables A.1, A.2, and A.3 illustrate this point by comparing the two measures for various groups of observations.

MEAN RESPONSE WHEN TOD RATES WERE INTRODUCED

If TOD rates affect electricity consumption patterns, then we expect relative peak load to decline on average when TOD rates are introduced and we expect relative peak load to fluctuate randomly about the previous year’s value when two non-TOD pricing years are observed. We calculate average response by doing weighted regressions of change
in relative peak load on three different sets of classificatory (dummy) variables. The weights are the initial-year average hourly loads for the full day.

Results of the first regression are presented in Table 3.2 using all 19,535 observations. The table shows weighted mean change in relative peak load for three sets of observations: continuing standard rates, introduction of TOD rates, and continuing TOD rates. The average response when TOD rates were first introduced was small—about a 1 percentage point reduction in relative peak load—but highly statistically significant. There is virtually no chance that the observed reduction could be the result of random fluctuations. In contrast, average changes in relative peak load under either continuing standard rates or continuing TOD rates were not significantly different from zero.

The second regression (Table 3.3) uses only the 3296 observations for when TOD rates were first introduced. It reports average response for each of the utilities and customer classifications for which we have observations both before and after the introduction of TOD rates. Most of the utility means are negative, and many are statistically significant. The two positive means are statistically indistinguishable from zero.

The third regression (Table 3.4) also uses the 3296 observations for introduction of TOD rates to calculate mean response by industrial category. For all but one category, response is negative as expected. For four SIC codes, the response is relatively large and statistically significant: wood products, primary metals, machinery manufacturing, and

Table 3.2
AVERAGE CHANGE IN RELATIVE PEAK LOAD
UPON INTRODUCTION OF TOD RATES

<table>
<thead>
<tr>
<th>Classification</th>
<th>Mean Change (percentage points)</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuing standard rates</td>
<td>0.07</td>
<td>(0.5)</td>
</tr>
<tr>
<td>Introduction of TOD rates</td>
<td>-0.97</td>
<td>(-7.3)</td>
</tr>
<tr>
<td>Continuing TOD rates</td>
<td>-0.12</td>
<td>(-1.4)</td>
</tr>
</tbody>
</table>
Table 3.3
CHANGE IN RELATIVE PEAK LOAD UPON INTRODUCTION OF TOD RATES, BY UTILITY

<table>
<thead>
<tr>
<th>Utility/Customer Classification</th>
<th>Mean Change (percentage points)</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCE/AA1</td>
<td>-1.43</td>
<td>(-3.6)</td>
</tr>
<tr>
<td>SCE/T73</td>
<td>-1.32</td>
<td>(-3.4)</td>
</tr>
<tr>
<td>DWP</td>
<td>-0.17</td>
<td>(-0.4)</td>
</tr>
<tr>
<td>PGE/A23</td>
<td>-1.89</td>
<td>(-3.6)</td>
</tr>
<tr>
<td>PGE/A22</td>
<td>-0.96</td>
<td>(-2.4)</td>
</tr>
<tr>
<td>WEP</td>
<td>-2.40</td>
<td>(-4.7)</td>
</tr>
<tr>
<td>MGE</td>
<td>-1.70</td>
<td>(-0.4)</td>
</tr>
<tr>
<td>WFL/CP4</td>
<td>-0.22</td>
<td>(-0.1)</td>
</tr>
<tr>
<td>LIL</td>
<td>0.13</td>
<td>(0.2)</td>
</tr>
<tr>
<td>CON</td>
<td>0.01</td>
<td>(0.0)</td>
</tr>
</tbody>
</table>

Table 3.4
CHANGE IN RELATIVE PEAK LOAD UPON INTRODUCTION OF TOD RATES, BY INDUSTRY

<table>
<thead>
<tr>
<th>Industrial Classification</th>
<th>Mean Change (percentage points)</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 Industrial nec</td>
<td>-0.54</td>
<td>(-1.2)</td>
</tr>
<tr>
<td>20 Food products</td>
<td>-0.66</td>
<td>(-1.0)</td>
</tr>
<tr>
<td>24 Wood products</td>
<td>-9.06</td>
<td>(-7.0)</td>
</tr>
<tr>
<td>26 Pulp and paper</td>
<td>-0.70</td>
<td>(-0.7)</td>
</tr>
<tr>
<td>28 Chemicals</td>
<td>-0.30</td>
<td>(-0.4)</td>
</tr>
<tr>
<td>29 Petroleum</td>
<td>-0.07</td>
<td>(-0.1)</td>
</tr>
<tr>
<td>30 Rubber and plastic</td>
<td>-1.94</td>
<td>(-1.9)</td>
</tr>
<tr>
<td>32 Stone, clay, glass</td>
<td>-0.39</td>
<td>(-0.6)</td>
</tr>
<tr>
<td>33 Primary metals</td>
<td>-4.84</td>
<td>(-7.1)</td>
</tr>
<tr>
<td>34 Fabricated metals</td>
<td>-0.53</td>
<td>(-0.6)</td>
</tr>
<tr>
<td>35 Machinery</td>
<td>-6.14</td>
<td>(-7.3)</td>
</tr>
<tr>
<td>36 Electrical machinery</td>
<td>-0.68</td>
<td>(-1.0)</td>
</tr>
<tr>
<td>37 Transportation equip</td>
<td>-0.96</td>
<td>(-1.8)</td>
</tr>
<tr>
<td>48 Communications</td>
<td>0.34</td>
<td>(0.4)</td>
</tr>
<tr>
<td>49 Utilities</td>
<td>-5.03</td>
<td>(-3.0)</td>
</tr>
<tr>
<td>All industrial</td>
<td>-1.33</td>
<td>(-7.3)</td>
</tr>
<tr>
<td>All commercial</td>
<td>-0.03</td>
<td>(-0.1)</td>
</tr>
</tbody>
</table>
utilities. Response by commercial customers is indistinguishable from zero. The mean response for industrial customers only was separately calculated to be $-1.33$ percentage points.

**Distributions of Response When TOD Rates Were Introduced**

In the previous subsection, we saw that large business customers reduced their relative peak loads by about 1 percentage point on average when TOD rates were introduced. Here we take a closer look at the distributions of changes in relative peak load, using the distributions to distinguish between “responsive” and “unresponsive” customers.

**Description of the Distributions**

A 1 percentage point average reduction in relative peak load could come about in many ways. For example, it could result if each and every customer reduced his relative peak load by 1 percentage point. Or it could equally well result if 1 percent of the customers reduced relative peak loads by 100 percentage points and the remaining 99 percent of customers did nothing at all. As we shall see, the actual situation is closer to the second example, in that the most responsive few percent of customers account for a large fraction of the total reduction in relative peak load.

Figure 3.2 is a histogram showing the distribution of change in relative peak load by all customers when TOD prices were introduced. The histogram is weighted by initial-year full-day average hourly consumption, to make it comparable with our preceding analysis. It shows that the great majority of customers exhibited fairly small changes; most of them fall in the “zero change” category, which in the histogram includes customers with changes between minus five and plus five percentage points. A few show up in the plus or minus ten percentage point categories, which also extend five points on either side of the designated midpoint. The number of customers making greater changes is so small that they get rounded to zero and do not show up on the histogram.

Customers making larger changes do appear on the separately plotted histograms for some particular industrial groups. For example,
Fig. 3.2—Distribution of change in relative peak load when
time-of-day prices were introduced (all customers)

Fig. 3.3 is a weighted histogram for SIC code 35, machinery manufacturers. Like Fig. 3.2, it shows that most customers made fairly small changes in relative peak load. However, a few firms that made reductions of about 80 percentage points show up at the far left of the figure.

Contributions to Reduction in Relative Peak Load

The distributions discussed above suggest that a handful of customers that made large changes in relative peak load when TOD prices were introduced accounted for much of the observed average reduction. Table 3.5 quantifies and supports that suggestion.

The first column in Table 3.5 lists the magnitudes of all changes by industrial customers that were actually observed. The changes are grouped into 10-percentage-point bands as in the histograms. Thus, a “0 percentage point change” includes any change between −5 and +5 percentage points, and a +30 change includes any between +25 and +35. The second column gives the number of observations falling in each category. The third column shows the weighted percentage of observations falling in each category, where the weights (as always) reflect initial-year full-day average hourly consumption. Like Fig. 3.2, this column shows that most customers made small changes; unlike Fig. 3.2, it also records the small fraction of customers that made larger changes.

The fifth column shows the contribution of each change category to the overall average change in relative peak load. The contribution is
Fig. 3.3—Distribution of change in relative peak load when time-of-day prices were introduced (machinery manufacturers)

defined as the percentage of the actually observed reduction in relative peak load that would have been observed if no one except customers in that change category had changed. The contribution is proportional both to the magnitude of the change and to the weighted number of observations in the change category. Thus, for example, although there is only a single firm (only three one-hundredths of one percent of all observations) in the -160 percentage point change category, the change that this firm made is so large that it accounts for 3.9 percent of the observed average change in relative peak load by all industrial customers. In contrast, although a weighted 82 percent of all firms are in the 0 percentage point change category, they contribute less than three times as much to the observed average change than does the single firm in the -160 category.

Responsive Firms Defined by Reference to Distributions of Response

We have suggested that a small fraction of responsive firms account for much of the observed average reduction in relative peak load. But how is a “responsive firm” to be identified? We describe one way in this subsection.

Here we define a responsive firm as one that reduces its relative peak load by more than some cutoff value. Thus, all firms to the left of some point in the distribution of change (for example, the histograms in Figs. 3.2 and 3.3) are responsive on this definition. We chose the cutoff point so that the net effect of the changes made by all firms
Table 3.5
DISTRIBUTION OF CHANGES IN RELATIVE PEAK LOAD BY
INDUSTRIAL CUSTOMERS WHEN TOD RATES
WERE INTRODUCED

| Change in Relative Peak Load (percentage points) | Customers | | | |
|---|---|---|---|---|---|
| Number | Weighted Percent | Standard Error | Contribution to Overall Change |
| -160 | 1 | 0.03 | (0.03) | -3.9 |
| -150 | -- | -- | -- | -- |
| -140 | 1 | 0.03 | (0.03) | -3.6 |
| -130 | -- | -- | -- | -- |
| -120 | -- | -- | -- | -- |
| -110 | 1 | 0.01 | (0.02) | -0.7 |
| -100 | 4 | 0.09 | (0.05) | -6.3 |
| -90 | 6 | 0.20 | (0.08) | -13.3 |
| -80 | 6 | 0.25 | (0.09) | -14.8 |
| -70 | 2 | 0.06 | (0.04) | -2.8 |
| -60 | 2 | 0.04 | (0.03) | -2.1 |
| -50 | 4 | 0.07 | (0.05) | -2.5 |
| -40 | 13 | 0.20 | (0.08) | -6.2 |
| -30 | 20 | 0.84 | (0.16) | -18.3 |
| -20 | 44 | 1.16 | (0.19) | -16.0 |
| -10 | 258 | 8.06 | (0.47) | -54.0 |
| 0 | 1669 | 82.05 | (0.67) | -11.0 |
| +10 | 208 | 5.85 | (0.41) | 35.7 |
| +20 | 36 | 0.73 | (0.15) | 10.5 |
| +30 | 11 | 0.20 | (0.08) | 4.3 |
| +40 | 5 | 0.06 | (0.04) | 2.0 |
| +50 | 2 | 0.04 | (0.03) | 1.4 |
| +60 | -- | -- | -- | -- |
| +70 | 1 | 0.01 | (0.02) | 0.5 |
| +80 | -- | -- | -- | -- |
| +90 | 1 | 0.02 | (0.02) | 1.2 |

to the right of that point is zero. That is, without the responsive firms (as we define them here), the (mean) overall response would be zero.

We can find the cutoff point by starting at the right end of the distribution and working our way to the left, adding up contributions until they net out to zero. The numbers in Table 3.5 help us to do that for Fig. 3.2. The contributions of all firms making positive changes is an increase in relative peak load of $35.7 + 10.5 + 4.3 + 2.0 + 1.4 + 0.5 + 1.2 = 55.6$ percentage points. Working our way up the list of negative contributions by firms that reduced their relative peak load, we find that the increase due to positive changes is offset by the time we
get partway through the -10 percent change category; -11.0 - 54.0 is
greater than 55.6. We draw the line within the -10 percent category at
the point where the changes just net out to zero. Beyond that point
(above it in Table 3.5; left of it in Fig. 3.2) are a weighted 3.9 percent
of all industrial customers. We define this 3.9 percent to be responsive,
and the 96.1 percent to their right in the histogram to be unresponsive.

The 3.9 percent of responsive firms account for the entire -1.33 per-
centage point average summer reduction in relative peak load by indus-
trial customers. Thus, we can calculate the average reduction for the
responsive firms as 1.33/0.039 = 34 percentage points. These numbers
are shown in Table 3.6, along with the results of similar calculations
for all customers (including commercial firms), and for individual two-
digit industrial groups.

Table 3.6 generally supports our characterization of the overall
reduction in relative peak load as being due to a small percentage of
responsive firms. In the handful of especially responsive industries,
however, the percentage of responsive firms (based on our present
definition) is considerably higher.

<table>
<thead>
<tr>
<th>Industrial Classification</th>
<th>Responsive Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Weighted Percent</td>
</tr>
<tr>
<td>All firms</td>
<td>2.7</td>
</tr>
<tr>
<td>All industrial firms</td>
<td>3.9</td>
</tr>
<tr>
<td>Industrial nec</td>
<td>2.2</td>
</tr>
<tr>
<td>20 Food products</td>
<td>4.6</td>
</tr>
<tr>
<td>24 Wood products</td>
<td>32.1</td>
</tr>
<tr>
<td>26 Pulp and paper</td>
<td>0.7</td>
</tr>
<tr>
<td>28 Chemicals</td>
<td>0.3</td>
</tr>
<tr>
<td>29 Petroleum</td>
<td>0.4</td>
</tr>
<tr>
<td>30 Rubber and plastic</td>
<td>5.4</td>
</tr>
<tr>
<td>32 Stone, clay, glass</td>
<td>0.9</td>
</tr>
<tr>
<td>33 Primary metals</td>
<td>17.8</td>
</tr>
<tr>
<td>34 Fabricated metals</td>
<td>0.7</td>
</tr>
<tr>
<td>35 Machinery</td>
<td>32.4</td>
</tr>
<tr>
<td>36 Electrical machinery</td>
<td>6.0</td>
</tr>
<tr>
<td>37 Transportation equip</td>
<td>1.0</td>
</tr>
<tr>
<td>48 Communications</td>
<td>--</td>
</tr>
<tr>
<td>49 Utilities</td>
<td>4.8</td>
</tr>
</tbody>
</table>
IV. REGRESSION ANALYSIS

We shall specify and estimate a model that allows firms in different industries to exhibit different degrees of response to peak prices. This model is suggested by the finding in Sec. III that some industries respond very little to TOD rates, while others respond much more. It seems sensible to suppose that firms in a responsive industry will be more sensitive to the level of peak prices than will firms in a non-responsive industry.

We have deliberately chosen to use an ad hoc model for this initial analysis of the ten-utility data base. More highly structured models based on production theory may unduly influence estimation results (Kohler et al., 1983); we prefer to let the data speak for themselves at this stage of the analysis.

THE MODEL

Consider a specific industrial firm. In general, that firm's relative peak load will be a function of many factors including the industrial processes it uses, the electricity prices it faces, peak-period definitions, detailed characteristics of the firm, weather conditions, demands for its products, prices of nonelectricity inputs, and a host of unquantifiable factors whose effects can be summarized by a random error term. This relationship can be expressed as an equation setting relative peak load equal to a possibly nonlinear function of the above variables. By subtracting last year's equation from this year's equation, we can in principle derive an equation that focuses directly on year-to-year changes in peak load. If the original equations are linear, then all of the right-hand side variables enter the new equation as year-to-year changes as well. Thus, any variables that do not change, such as certain characteristics of the firm, and the intercept term, drop out of the difference equation. This has the important advantage that persistent, but unmeasurable, individual firm effects no longer complicate the estimation.

If the original functions are nonlinear, however, things can get very complicated. Then the right-hand side of the difference equation is the difference of two nonlinear functions. This has two implications. First, unchanging variables do not necessarily drop out of the differ-
ence equation. Second, the equation may be very complex and difficult to estimate.

We elect to cut through these complexities by specifying directly an equation to explain changes in relative peak load. Our specification should be thought of as a simple approximation to the more complex equation that would result from the derivation sketched above.

**Functional Form**

We specify a model of the general form

\[ \text{Change in relative peak load} = (aS)(bX) + cZ, \]

where \( S \) is a 16-vector of dummy variables for two-digit SIC codes, 15 of them for the industrial classifications listed in Table 3.6 and one for all commercial classifications grouped together;

\( a \) is a vector of SIC response coefficients to be estimated;

\( X \) is a vector of explanatory variables including prices and other variables to be described below;

\( b \) is a vector of coefficients for \( X \) to be estimated;

\( Z \) is another vector of explanatory variables, which may include some of the same variables that are in \( X \);

\( c \) is a vector of coefficients for \( Z \).

Written out in full, the expression on the right-hand side of the equation is

\[ (a_1S_1 + \cdots + a_{16}S_{16})(b_1X_1 + \cdots + b_nX_n) + (c_1Z_1 + \cdots + c_mZ_m), \]

where there are \( n \) explanatory variables in \( X \) and \( m \) in \( Z \).

Here is a simple example to explain the advantages of the multiplicative form \( (aS)(bX) \). (Ignore the additive term \( cZ \) for the moment.) In the example, there are only two industries and two utilities. Industry A uses some processes that can easily be shifted to off-peak hours, while industry B finds it difficult or impossible to alter its daily consumption pattern. Utility 1 introduces a 2-cent peak-period price differential, while utility 2 adopts a differential only half as large. Price is the only explanatory variable included in \( X \). A plausible pattern of response (change in relative peak load) for this situation would be:

<table>
<thead>
<tr>
<th>Utility</th>
<th>Industry A</th>
<th>Industry B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility 1</td>
<td>-20</td>
<td>0</td>
</tr>
<tr>
<td>Utility 2</td>
<td>-10</td>
<td>0</td>
</tr>
</tbody>
</table>
That is, response is proportional to price and much larger in industry A than in industry B. The multiplicative form can fit this situation exactly with \( a = (-20, 0) \) and \( b = 0.5 \).

The best that an additive specification \( aS + bX \) can do is \( a = (-7.5, 7.5) \) and \( b = -5 \). That underestimates the effect of the difference in utility 1 and utility 2's prices in industry A, and overestimates the effect of that difference in industry B, as shown in this table of fitted response:

<table>
<thead>
<tr>
<th></th>
<th>Industry A</th>
<th>Industry B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility 1</td>
<td>-17.5</td>
<td>-2.5</td>
</tr>
<tr>
<td>Utility 2</td>
<td>-12.5</td>
<td>2.5</td>
</tr>
</tbody>
</table>

In accordance with our expectations, we find in estimating the model in the next section using real data that the multiplicative form is much more successful in explaining response than is an additive form alone.\(^1\) We allow for the possibility that there may be additive effects as well as multiplicative effects by including the additive term \( cZ \) in the estimating equation.

**Explanatory Variables**

The explanatory variables that may enter the vectors \( X \) and \( Z \) include:

- \( PK \)  The change in peak period energy price differential from one year to the next. We first calculate the prices per kwh facing each customer each month, including fuel price adjustments, high voltage discounts, etc. The peak differential each month is the peak-period energy price less the offpeak-period energy price. (The differential is zero under standard rates.) We then divide each differential by the implicit GNP deflator for that month (with a base of 1.00 in the first quarter of 1976) to express the price in constant dollars. Finally, we subtract last year's differential from this year's differential to get \( PK \). The result will be zero during years in which standard rates continue in effect, positive when TOD rates are first introduced, and either positive or negative,

\(^1\)An estimate of the additive specification is in Appendix Table A.4. It explains only about half as much of the variance in change in relative peak load as does the corresponding multiplicative specification.
but usually close to zero, under continuing TOD rates. The units of $PK$ are 1976 cents.\footnote{We do not include lagged prices in our estimating equation, so the equation will not detect any delayed (more than one year) response to TOD rates. This is not a serious problem in our case, because as Table 3.2 indicates, there is little or no delayed response in our data.}

$PD$ The change in peak-period demand price. We start with the peak-period demand price per kw facing each customer each month, after taking into account any applicable discounts. (We consider a noncoincident demand charge with an offpeak waiver to be the same as a peak demand charge.) We then deflate it using the implicit GNP deflator and calculate the change from last year to this year. The result will generally be positive when TOD rates are first introduced, and close to zero in other years. The units of $PD$ are 1976 dollars.

$PN$ The change in noncoincident demand price. We start with the noncoincident demand price per kw facing each customer each month, again accounting for any applicable discounts. After deflating by the implicit GNP deflator, we calculate the year to year change. The result will be negative when introduction of TOD rates substitutes a peak demand charge for a noncoincident demand charge, and generally close to zero otherwise. The units of $PN$ are 1976 dollars.

$PKHRS$ The number of hours per weekday in the peak period. This differs from one utility to another, and may differ between summer and winter months for utilities whose tariffs have seasonal differences. It is a constant for a given utility during a given season; for standard rate observations, we use the value that will apply when TOD rates later come into effect. The units of $PKHRS$ are hours.

$SHORT$ A dummy variable equal to one for utilities with short peak periods (eight hours or less), and equal to zero for utilities with longer peak periods.

$SIZE$ A measure of customer size. We use average weekday hourly kwh consumption during the first of the pair of years used to calculate change in relative peak load,
divided by 1000. Thus the units of SIZE are thousands of kwh per hour.

SIZE_SQ The square of SIZE is included to allow for possible non-linearities in the effect of SIZE on change in relative peak load.

HEAT Change in heating degree days per month. We identified the major weather station that is closest to each customer and calculated a weighted average of reported calendar-month heating degree days, with the weights being the number of days from each calendar month in that customer's billing month. This year's value less last year's value divided by 100 equals HEAT. Winter months will have positive values of HEAT if this year is generally colder than last year, and negative values if it is generally warmer. During the summer, HEAT will generally be calculated as the difference between two small or zero values, and hence it will be close to zero itself. The units of HEAT are hundreds of heating degree days.

COOL The change in cooling degree days. This is calculated in a way that parallels the calculation of HEAT. The units of COOL are hundreds of cooling degree days.

MDWST A dummy variable that equals one if the observation is for a customer in the Midwest (Wisconsin, Michigan, or Illinois), and zero otherwise. This and the following dummy variable are meant to control for unmeasured regional effects.

NYORK A dummy variable that equals one if the observation is for a customer in New York, and zero otherwise.

W77 A dummy variable that equals one if the observation is for winter 1977, and zero otherwise. This and the following dummy variables are meant to control for unmeasured seasonal and other temporal effects.

S78 through W80 are similarly defined for observations during summer 1978 through winter 1980.
Estimating Methods

Our model is not suitable for ordinary least squares estimation because it is nonlinear in the coefficients. Three alternative estimation methods are available, depending on the resources available for estimation. In all three methods, we weight the observations by each customer's initial-year full-day average weekday electricity consumption in order to approximate the class average response.

1. **Two-stage estimation.** In the first stage of a two-stage procedure, we obtain an estimate of the vector of SIC group response coefficients $a$ by regressing change in relative peak load on the vector of SIC dummies $S$, using only the 3296 observations for years when TOD rates were first introduced. Using estimated values of $a$, we calculate a scalar value $aS$ for each observation and multiply it times the vector of explanatory variables $X$ to create transformed variables $(aS)X$. The coefficient vectors $b$ and $c$ are then estimated in a second-stage linear regression of change in relative peak load on $(aS)X$ and $Z$, using all 19,535 observations.

While this is a relatively inexpensive way to proceed, the two-stage estimates are biased because the first-stage estimate of $a$ does not control for prices and other explanatory variables. These variables are almost certainly correlated with the industry dummies, because industry mix differs from one utility to another.

2. **Iterative linear estimation.** An iterative extension of the two-stage method would converge to nonlinear least squares estimates if continued long enough. This method uses the two-stage estimate of $b$ just described to calculate scalar multipliers $bX$ and hence transformed SIC dummies $(bX)S$. We then perform a linear regression of change in relative peak load on $(bX)S$ and $Z$ (using all 19,535 observations), yielding a revised estimate of $a$, which can then be used to calculate new transformed variables $(aS)X$ for a new regression of change in relative peak load on $(aS)X$ and $Z$, and so on until the estimates stop changing from one iteration to the next or the iteration limit is reached.

Iterative estimation (and the following method, full nonlinear estimation) require that we impose one constraint on either vector $a$ or vector $b$. Without a constraint, $a$ and $b$ are identified only up to a scalar multiple. For example, if $a^*$ and $b^*$ minimize the sum of squared residuals, then so do $2a^*$ and $.5b^*$. We constrain the elements of $a$ to be consistent with the overall average response of $-.97$ percentage points. That is, we impose the following constraint on the coefficients:
\[ w_1a_1 + w_2a_2 + \cdots + w_{16}a_{16} = -0.97, \]

where the \( w_i \) are weights equal to each SIC code's proportion of initial-year consumption in the 3296 observations for introduction of TOD rates.

3. Full nonlinear estimation. The model can also be estimated directly using a nonlinear regression program such as the SAS procedure NLIN, with a constraint on the elements of \( \alpha \). With many variables and many observations, this alternative is prohibitively expensive, unless the starting values for the estimates are very close to their final values. We use estimates from the iterative procedure (after 15 full iterations) as starting values for the full nonlinear estimation.\(^3\)

The nonlinear estimation method is unbiased, because it does control for prices and other effects when estimating industry specific response, and for industry mix when estimating price coefficients. It also yields better (asymptotically correct) estimates of standard errors. Standard errors for price coefficients calculated in the two-stage procedure are conditional on the first-stage estimates of industry-by-industry response; the nonlinear procedure calculates unconditional standard errors.

In the next subsection, we present two-stage estimates for several alternative specifications (lists of explanatory variables). For one of the specifications, we also present full nonlinear estimates. The nonlinear estimates are quite close to the two-stage estimates, indicating that the bias in the two-stage estimates is not severe.

THE RESULTS

First-Stage Estimates of Industry Effects Using the Two-Stage Estimation Method

The first-stage estimates of the individual SIC code response coefficients \( \alpha \) are the average percentage points of change in relative peak load for each two-digit SIC code, calculated using 3296 observations made when TOD rates were first introduced. These were reported in Table 3.4 above. They are also repeated, together with full nonlinear estimates for comparison, in Table 4.2 below.

\(^3\)Our SAS programs to do the iterative and nonlinear estimation are listed in Appendix B.
Second-Stage Estimates of Price and Other Effects
Using the Two-Stage Estimation Method

The second-stage estimates of the coefficients of prices and other explanatory variables (b and c) are shown in Table 4.1 for a series of increasingly complex specifications. Specifications (1) through (5) estimate the effects of the multiplicative X variables only; the additive Z variables are omitted from these first five specifications. Specification (1) includes only prices in X. The estimated coefficients are all positive and significant. The positive price coefficients may seem at first glance to have the wrong sign, but in fact they reflect normal economic behavior, as discussed below.

Specifications (2) through (5) include successively more explanatory variables in X: PKHRS and SHORT to capture the effect of the length of the peak pricing period, SIZE and SIZE SQ to measure the (possibly nonlinear) effect of customer size, HEAT and COOL to capture the effects of weather, and finally in (5) a set of regional and temporal dummy variables to control for the effects of other influences that are not captured by the preceding scaled variables.

Specification (6) includes for the first time a number of explanatory variables in the additive term cZ. In specifying equation (6), we divided our explanatory variables between X and Z according to our a priori notions of which ones would most likely affect response proportionately for all SIC codes (X) and which would tend to affect all SIC codes by equal additive amounts (Z). It turned out that our a priori notions were wrong; the multiplicative specification (5) explains half again as much variance as does the combined specification (6). Finally, specification (7) recognizes that all of the explanatory variables may have both multiplicative and additive effects, and includes them all in both X and Z.

Full Nonlinear Estimates

We made full nonlinear estimates of one of the smaller specifications, specification (3), using iterative estimates as starting values. Our aim was to see if the estimates changed very much from the two-stage estimates.

The two estimates of industry effects are compared in Table 4.2. The estimates are broadly similar. Industries that appear to be particularly responsive in the two-stage procedure also generally appear to be responsive in the nonlinear estimates. The sole exception is SIC code 49, utilities, which goes from significantly negative to insignificantly positive. Three additional industries—food products, rubber and
<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
<td>b</td>
</tr>
<tr>
<td>INTERCEPT</td>
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<td>2.011</td>
<td>2.084</td>
<td>2.086</td>
<td>0.381</td>
<td>1.677</td>
<td>0.951</td>
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<tr>
<td></td>
<td>(4.3)</td>
<td>(6.4)</td>
<td>(6.7)</td>
<td>(6.7)</td>
<td>(0.9)</td>
<td>(5.1)</td>
<td>(2.7)</td>
</tr>
<tr>
<td>PK</td>
<td>0.390</td>
<td>0.558</td>
<td>0.661</td>
<td>0.658</td>
<td>0.361</td>
<td>0.580</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(7.2)</td>
<td>(6.8)</td>
<td>(8.1)</td>
<td>(8.0)</td>
<td>(4.3)</td>
<td>(7.0)</td>
<td>(4.3)</td>
</tr>
<tr>
<td>PD</td>
<td>0.364</td>
<td>0.373</td>
<td>0.350</td>
<td>0.349</td>
<td>0.351</td>
<td>0.376</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(9.2)</td>
<td>(9.5)</td>
<td>(8.9)</td>
<td>(8.9)</td>
<td>(8.2)</td>
<td>(9.3)</td>
<td>(8.0)</td>
</tr>
<tr>
<td>PN</td>
<td>0.236</td>
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<td>(6)</td>
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<td>0.617</td>
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<tr>
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<td>0.399</td>
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</tr>
<tr>
<td>W79</td>
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<td>--</td>
<td>--</td>
<td>--</td>
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<td>0.075</td>
<td>-0.882</td>
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<td></td>
<td>(0.4)</td>
<td>(-2.2)</td>
</tr>
<tr>
<td>S80</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.852</td>
<td>0.598</td>
</tr>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td>(-4.5)</td>
<td>(1.6)</td>
</tr>
<tr>
<td>W80</td>
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<td>1.127</td>
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<td>R_SQ</td>
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<td>0.0220</td>
<td>0.0220</td>
<td></td>
<td>0.0537</td>
<td>0.0355</td>
</tr>
</tbody>
</table>

NOTE: Dependent variable is change in relative peak load; t-statistics are in parentheses.
### Table 4.2
COMPARISON OF FIRST-STAGE ESTIMATES FROM THE
TWO-STAGE PROCEDURE AND FULL NONLINEAR
ESTIMATES OF INDUSTRY EFFECTS

<table>
<thead>
<tr>
<th>Industrial Classification</th>
<th>First Stage</th>
<th></th>
<th>Nonlinear</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>t-stat.</td>
<td>Coeff.</td>
<td>t-stat.</td>
</tr>
<tr>
<td>Industrial nec</td>
<td>-0.544</td>
<td>(-1.2)</td>
<td>-0.472</td>
<td>(-1.6)</td>
</tr>
<tr>
<td>20 Food products</td>
<td>-0.655</td>
<td>(-1.0)</td>
<td>-1.198</td>
<td>(-2.6)</td>
</tr>
<tr>
<td>24 Wood products</td>
<td>-9.063</td>
<td>(-7.0)</td>
<td>-14.502</td>
<td>(-6.9)</td>
</tr>
<tr>
<td>26 Pulp and paper</td>
<td>-0.696</td>
<td>(-0.7)</td>
<td>-0.524</td>
<td>(-0.6)</td>
</tr>
<tr>
<td>28 Chemicals</td>
<td>-0.296</td>
<td>(-0.4)</td>
<td>-0.098</td>
<td>(-0.2)</td>
</tr>
<tr>
<td>29 Petroleum</td>
<td>-0.072</td>
<td>(-0.1)</td>
<td>0.088</td>
<td>(0.3)</td>
</tr>
<tr>
<td>30 Rubber and plastic</td>
<td>-1.941</td>
<td>(-1.9)</td>
<td>-2.677</td>
<td>(-3.7)</td>
</tr>
<tr>
<td>32 Stone, clay, glass</td>
<td>-0.392</td>
<td>(-0.6)</td>
<td>-0.835</td>
<td>(-1.3)</td>
</tr>
<tr>
<td>33 Primary metals</td>
<td>-4.839</td>
<td>(-7.1)</td>
<td>-6.207</td>
<td>(-8.7)</td>
</tr>
<tr>
<td>34 Fabricated metals</td>
<td>-0.531</td>
<td>(-0.6)</td>
<td>-0.823</td>
<td>(-1.4)</td>
</tr>
<tr>
<td>35 Machinery</td>
<td>-6.142</td>
<td>(-7.3)</td>
<td>-3.448</td>
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</tr>
<tr>
<td>36 Electrical machinery</td>
<td>-0.685</td>
<td>(-1.0)</td>
<td>-1.007</td>
<td>(-1.8)</td>
</tr>
<tr>
<td>37 Transportation equipment</td>
<td>-0.963</td>
<td>(-1.8)</td>
<td>-0.857</td>
<td>(-3.3)</td>
</tr>
<tr>
<td>48 Communications</td>
<td>0.336</td>
<td>(0.4)</td>
<td>0.125</td>
<td>(0.3)</td>
</tr>
<tr>
<td>49 Utilities</td>
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<td>(0.9)</td>
</tr>
<tr>
<td>Commercial</td>
<td>-0.031</td>
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<td>0.063</td>
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</table>

**NOTE:** Dependent variable is change in relative peak load (percentage points).

plastic, and transportation equipment—that were at best marginally significant in the first-stage estimates, show up with strongly significant responses in the nonlinear estimates.

The two estimates of price and other effects are compared in Table 4.3. The coefficients are changed very little in the full nonlinear estimates. Estimated significance levels are slightly lower, reflecting the fact that the second-stage coefficients are conditional on the first-stage industry effects estimates, while the nonlinear coefficients are estimated simultaneously with the industry effects.

Based on these results, we believe that full nonlinear estimates of the other specifications would show (1) industry effects similar to the nonlinear estimates in Table 4.2 and (2) price and other effects similar to the two-stage estimates for each specification in Table 4.1, but with slightly lower t-statistics.
Table 4.3
COMPARISON OF SECOND-STAGE ESTIMATES FROM THE
TWO-STAGE PROCEDURE AND FULL NONLINEAR
ESTIMATES OF PRICE AND OTHER EFFECTS

<table>
<thead>
<tr>
<th>Variable</th>
<th>Second Stage</th>
<th>Nonlinear</th>
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<td></td>
<td>Coeff. t-stat.</td>
<td>Coeff. t-stat.</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.084 (6.7)</td>
<td>2.159 (6.4)</td>
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<tr>
<td>PK</td>
<td>0.661 (8.1)</td>
<td>0.663 (6.8)</td>
</tr>
<tr>
<td>PD</td>
<td>0.350 (8.9)</td>
<td>0.307 (7.1)</td>
</tr>
<tr>
<td>PN</td>
<td>0.215 (4.3)</td>
<td>0.184 (3.8)</td>
</tr>
<tr>
<td>FKhRS</td>
<td>-0.165 (-6.7)</td>
<td>-0.160 (-6.2)</td>
</tr>
<tr>
<td>SHORT</td>
<td>-1.351 (-7.3)</td>
<td>-1.482 (-6.9)</td>
</tr>
<tr>
<td>SIZE</td>
<td>0.0219 (8.2)</td>
<td>0.0189 (6.4)</td>
</tr>
<tr>
<td>SIZE2</td>
<td>-0.000118 (-6.1)</td>
<td>-0.000112 (-5.8)</td>
</tr>
</tbody>
</table>

Discussion

Differences Among the Various Specifications. The estimated effects of prices and other variables in specifications (1) through (4) and (6) are similar; these five specifications do not include the dummy regional and temporal variables in the multiplicative term bX. Also, the results for specifications (5) and (7) are similar; these do include the dummy variables in the multiplicative term. There are more substantial differences in estimates (particularly for the coefficients of PK and PN) between these two sets of estimates.

There is only one first-stage estimate of industry effects for all seven specifications, but the estimated industry effects differ somewhat between the two-stage and the full nonlinear estimates.

Which set of estimates is “best”? On purely statistical grounds, one would have to choose specification (7) over the other specifications. The regional and temporal dummy variables are clearly significant as a group in both the multiplicative and the additive portions of (7). Including them controls to some extent for unmeasured effects such as fluctuations in economic activity; omitting them biases the estimates of the coefficients of any variables that are correlated with the dummies. However, when we attempted to use specification (7) for prediction

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4This statement is true for specification (3) whether it is estimated by the two-stage method or the full nonlinear method. Presumably, nonlinear estimates for the other specifications would also be similar to the corresponding two-stage estimates.
(Park and Acton, forthcoming), we found that it performed substantially worse than did simpler specifications. Consequently, we shall discuss the results of all seven specifications, without singling out (7) for special emphasis.

Also on statistical grounds, one would have to choose the nonlinear estimates of industry effects over the two-stage estimates, since the two-stage estimates are biased by failure to control for the effect of prices and other variables. The two industry-effects estimates perform about equally well for prediction purposes.

**Price Effects.** We expect that a larger increase in peak price will result in a larger decrease in relative peak load, and that is precisely what the estimated price coefficients imply. A positive coefficient multiplied by a larger peak price increase will yield a larger (positive) multiplier $bX$. The larger multiplier times the (negative) SIC-specific change in relative peak load $aS$ yields a larger decrease in relative peak load for larger price increases.

For example, consider the estimate of our simplest model, specification (1). What is the estimated effect of the following price change: a 1 cent increase in energy price differential, a $1 increase in peak demand charge, and no change in the noncoincident demand charge? That price change corresponds to values of $PK = 1$, $PD = 1$, and $PN = 0$. Thus the multiplier $bX = 0.125 + 0.590 \times 1 + 0.364 \times 1 + 0.236 \times 0 = 1.079$, so the model predicts 1.079 times the standard SIC-specific response for each SIC code. For primary metals, that equals $1.079 \times (-4.839) = -5.221$, or a little over a 5 percentage point decrease in relative peak load. For rubber and plastic manufacturers, it is only $1.079 \times (-1.941) = -2.094$, or about a 2 percentage point decrease in relative peak load. Twice the postulated price change would give a multiplier $bX = 0.125 + 0.590 \times 2 + 0.364 \times 2 + 0.236 \times 0 = 2.033$, and correspondingly larger decreases in relative peak load.

The price coefficients are estimated with surprising precision and are reasonably robust across the various specifications. This is particularly true for the coefficient of $PD$, the peak demand price. A $1 increase in peak demand price contributes between .34 and .38 to the response multiplier $bX$ in all seven specifications. The coefficient of the energy price differential $PK$ is more variable, but always significantly positive, with a range from .36 to .66. It is questionable whether an increase in noncoincident demand charge $PN$ significantly decreases relative peak load. The coefficient of $PN$ is always positive, as expected, but not significantly greater than zero in the two equations that control for unmeasured regional and temporal multiplicative effects, (5) and (7).
Comparing Energy and Demand Price Effects. The coefficient of \( PK \) is always greater than the coefficient of \( PD \). Does that mean that an energy charge is more effective at reducing relative peak load than is a demand charge? Not necessarily. It means only that a 1 cent increase in a kwh charge has a larger effect than does a $1 increase in a kw charge. More is needed to support statements about the relative effectiveness of the two prices.

One way to make the comparison is to calculate elasticities of relative peak load (\( RPL \)) with respect to the various prices.\(^5\) In our model these elasticities are not constant; rather, their values depend on the values of other variables. The elasticity with respect to a particular price \( p \) (energy, peak demand, or noncoincident demand) is:

\[
\text{elasticity} = \frac{\text{change in } RPL}{\text{change in } p} \cdot \frac{p}{RPL} = (aS) b_p(p/RPL),
\]

where \( b_p \) is the coefficient for the particular price and \( p \) is its level. Evaluating the elasticity expression at the overall average values for \( aS \) (about a 1 percent decrease, or \(-0.01\)), \( p \) (peak energy price = 4 cents, peak demand charge = $4, and noncoincident demand charge = $1), and relative peak load = 1.1, gives the generally small elasticities shown in Table 4.4.\(^5\)

Another way to compare the effectiveness of the different prices is to make the comparison for prices that raise the same revenue. A 1 cent peak energy price differential applies to many hours throughout the month. For example, an eight-hour weekday peak will typically apply for \( 8 \times 21 = 168 \) hours a month, and thus contribute $1.68 for each average peak hourly kwh. In contrast, a peak demand charge

<table>
<thead>
<tr>
<th>With respect to</th>
<th>Specification</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
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<td>PK</td>
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<td>-0.020</td>
<td>-0.024</td>
<td>-0.024</td>
<td>-0.013</td>
<td>-0.021</td>
<td>-0.013</td>
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<tr>
<td>PD</td>
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<td>-0.013</td>
<td>-0.014</td>
<td>-0.013</td>
<td>-0.013</td>
<td>-0.013</td>
<td>-0.014</td>
<td>-0.013</td>
</tr>
<tr>
<td>PN</td>
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<td>-0.002</td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.002</td>
<td>-0.000</td>
</tr>
</tbody>
</table>

\(^5\)If total consumption is constant, elasticities of relative peak load are equal to conventional own price elasticities of peak-period energy consumption.

\(^6\)Note that these are short-run elasticities, reflecting changes observed during the first year TOD rates were in effect. Long-run elasticities may well be larger (in absolute value).
applies only once, to the maximum demand at any time during peak hours during the month. Say the peak period load factor is .8; then the maximum demand is \(1/0.8 = 1.25\) for each average hourly kwh, and a peak demand charge of \$1\) would contribute \$1.25 for each average peak hourly kwh. To match the contribution of a 1 cent energy price differential, the demand charge would have to be larger than \$1\); specifically, it would have to equal \((168/125) \times \$1 = \$1.34\). Thus the effects of demand charges that raise the same revenue as a 1 cent energy price differential would be somewhat larger than the relative size of their coefficients in Table 4.1 indicates. Coefficients adjusted to show the effects of “equal revenue” prices are shown in Table 4.5.

**Effects of Non-Price Variables.** Turning now to the other (nonprice) coefficients reported in Table 4.1, look first at those that measure the effect of length of peak period, \(PKHRS\) and \(SHORT\). The results for specifications without regional and temporal dummy variables in the multiplicative factor \(bX\) (specifications 1–4, 6) consistently suggest that the response (reduction in relative peak load) is less for tariffs with eight hour or shorter peak periods, but that within both short and long peak tariffs, the response is less, the longer the peak period. The same pattern is present, but weaker, in the other two specifications. (Note that positive coefficients work in opposite directions in the multiplicative term \(bX\) and the additive term \(cZ\). In \(bX\), a positive coefficient means a larger response; in \(cZ\), it means a smaller response.)

The significant positive coefficient of \(SIZE\) in all specifications indicates that larger customers respond on average more than smaller customers. The negative coefficient of \(SIZE_{-SQ}\) (significant except in

<table>
<thead>
<tr>
<th>Specification</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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</thead>
<tbody>
<tr>
<td>(PK)</td>
<td>0.590</td>
<td>0.558</td>
<td>0.661</td>
<td>0.658</td>
<td>0.361</td>
<td>0.580</td>
<td>0.360</td>
</tr>
<tr>
<td>(PD)</td>
<td>0.489</td>
<td>0.501</td>
<td>0.470</td>
<td>0.469</td>
<td>0.472</td>
<td>0.505</td>
<td>0.464</td>
</tr>
<tr>
<td>(PN)</td>
<td>0.317</td>
<td>0.327</td>
<td>0.289</td>
<td>0.286</td>
<td>0.095</td>
<td>0.267</td>
<td>0.070</td>
</tr>
</tbody>
</table>
specification (7)) suggests that response increases at a decreasing rate as SIZE increases.

Except in the two specifications that control for unmeasured regional and temporal effects (5 and 7), the coefficients of the weather variables HEAT and COOL are insignificant or erratic. But in those two equations they are negative and significant, suggesting that extremes of heat or cold both tend to increase relative peak load.
V. EVALUATING TOD PRICING FOR U.S.
BUSINESS CUSTOMERS

Ratemaking often reflects several considerations and may include one or more of the following objectives:

- Adopting rates that more accurately reflect costs,
- Implementing new rates where benefits exceed the incremental metering costs, and
- Causing a deliberate redistribution of costs among customers.

The first objective enjoys wide support. Selecting rates which more accurately reflect costs serves two important goals of ratemaking: fairness and efficiency. A rate is often judged to be fair if it charges customers in proportion to the costs they impose on the utility system. If costs vary by time of use, and rate structures do not reflect that time-of-use variation, then some customers are necessarily subsidizing other customers whose pattern of usage is above average in costliness. Reducing this cross-subsidy promotes fairness. Efficiency is also encouraged by a rate structure that reflects the finer breakdown of cost variation. For example, we do not wish to encourage consumption by customers who do not value the electricity as much as the marginal costs of supplying it; conversely we do not wish to overprice electricity so that we discourage use by some customers who are willing to pay an amount greater than the marginal costs of supplying it. If it were costless to introduce TOD pricing and the regulator wished to pursue this objective of more accurate pricing, then TOD rates would be justified whether or not customers were expected to alter their consumption patterns.

The second objective is rooted in formal welfare economics: A new rate structure whose benefits exceed the incremental metering costs is deemed an improvement in social policy because it serves the first objective—accurate reflection of costs—while assuring that, in net, the use of resources is improved. We will describe this second criterion in more detail in the next subsection and apply it to TOD rates using the empirical findings of this report.

The third objective attempts to cause deliberate redistribution of costs among customers. Lifeline rates or surcharges for use above some level are examples of such rate structures. These are conscious attempts to affect the distribution of purchasing power and—like
questions of income distribution—they properly belong in the sphere of political decisionmaking. Economists can help identify the efficiency and distributional consequences of alternative redistribution policies, but they are not especially qualified to judge the desirability of one distribution over another. We will not discuss any further rates that deliberately redistribute costs beyond what is implied by making prices more accurately reflect the costs of supply.

DEFINITION OF BENEFIT/COST CRITERIA

Under a formal welfare economics standard, the decision in any particular instance to introduce TOD rates depends on the costs of the utility system involved (including both its historic accounting costs and the marginal costs of generation and expansion), amount and pattern of demand by individual customers, and the price responsiveness of customers if new rate levels or rate structures are introduced.

It lies beyond the scope of the present analysis to conduct a thorough examination of costs. We will assume that the rate structures approved by regulators are reasonable approximations to the relevant costs. We also assume that all other goods are correctly priced.

The suitable standard of evaluation is to compare changes in producer’s and consumers’ surplus with incremental metering costs. Harberger (1971) and Turvey (1974) describe this formal welfare criterion, and Acton and Mitchell (1983) lay out the details as applied to electricity. We will not reproduce that derivation here but only summarize it in Fig. 5.1. When a utility switches from average cost pricing (at \( p \)) to TOD pricing where price equals marginal cost in each time period \( (p_1^* \text{ and } p_2^* \text{ in Fig. 5.1}) \), the gains in well-being in peak and offpeak periods are shown as areas \( Y_1 \) and \( Y_2 \), respectively. The gain in producer’s surplus is the change in costs of supply less the change in revenue. The change in consumers’ surplus is the change in the amount a customer would be willing to pay less the change in amount actually charged. The total gain in welfare is the sum of producer’s and consumer’s gains. In Fig. 5.1 the net gain in the peak period is shown as area \( Y_1 \), which equals the gain in producer’s surplus of

\[ \text{\footnotesize{At present we are describing welfare changes as if areas under demand curves measure directly changes in consumer surplus. In a moment we will elaborate the discussion to include the intermediate good, electricity, which serves as an input to goods that yield direct satisfaction. We shall also assume for the moment that price in one period has no effect on demand for electricity in the other period; this assumption is also relaxed in the more detailed discussion below.}} \]
Fig. 5.1—Net changes in welfare in peak and off-peak periods

(a) Peak

(b) Off-peak
$X_1 + Y_1$ (the amount of costs of production not previously recovered under average cost pricing) less the loss in consumer surplus of $X_1$. In the offpeak period, consumers’ surplus increases by $X_2 + Y_2$, and producer’s surplus decreases by $X_2$, for a net gain in this period of $Y_2$.

Two important features of the demand for electricity distinguish welfare analysis of TOD price changes from price changes applied to many other goods: First, electricity is an intermediate good; second, TOD pricing involves two price changes, a peak and offpeak price, rather than the more familiar case where one price changes and all other prices remain the same. Both features complicate the analysis, but they do not alter the fundamental picture just presented. Furthermore, the empirical characteristics of the present situation make possible relatively simple measures that are close approximations to what even the most refined measures would yield.

**Electricity As an Intermediate Good**

First, electricity consumption does not yield direct utility; rather it is an input to goods and services that yield utility when used. Therefore, changes in electricity prices affect the profit of the producer of final goods as well as the welfare of its consumers. The areas to the left of the demand curve in Fig. 5.1 measure changes in benefit to these final producers plus consumers if the market for the final good is competitive (Kohler, 1981). If this market for final goods is not competitive, then the areas to the left of electricity demand curves understate the gains or losses in welfare. The degree to which changes in welfare are understated depends on the competitiveness of the final goods market: when the final market is perfectly competitive, there is no understatement; when it is perfectly collusive, there is some understatement whose magnitude is inversely related to the profitability of the sellers (Quirmbach, 1983).

We use the area to the left of the demand curve for electricity as a direct measure of welfare and believe it is likely a good approximation to the final good amounts for two reasons. First, the final markets for many industries studied appear to be competitive; they include industries such as food products, wood products, pulp and paper, building

---

2There may be a small approximation error in this formulation, which does not account for the income effect of the price change. However, the relatively small price elasticities, along with the small share of expenditures devoted to electricity, makes this approximation error negligible. See Willig (1979) for a general discussion of the use of consumer surplus in such circumstances, and Lillard and Acton (1981) for a specific comparison of this measure with exact measures of welfare change applied to residential electricity demand.
materials, machinery, and so forth. Second, any understatement of welfare changes is mitigated by the fact that TOD pricing raises peak price and lowers offpeak price, leading to gains in one period and losses in the other which at least partially offset any error.

**Measuring Welfare When Two Prices Change**

The second important feature of welfare measurement applied to TOD electricity pricing is that TOD pricing involves simultaneous changes in two or more prices. If one period's price had no effect on another period's consumption, then measuring areas to the left of the demand curves would be relatively simple. In many cases, however, the demand for electricity in one period of the day will be importantly affected by the price in another period of the day. In general, raising the peak price will increase offpeak consumption and lowering the offpeak price will lower peak period consumption. The implications for measuring the relevant areas under demand curves are shown in Fig. 5.2. The curves $D^p_1$ and $D^*_1$ represent demand in the peak period and $D^b_2$ and $D^*_2$ demand in the offpeak period. The curves designated with superscript $b$ are constructed on the assumption that price in the other period of time remains at $p$, the non-TOD price level. The curves designated with an * are constructed on the assumption that price in the other period of time is set to $p^*$, the level under TOD pricing. The curve $D^*_1$ lies to the left of $D^b_1$ whenever peak-period usage is shifted to offpeak use at a lower price. Correspondingly, the curve $D^*_2$ lies to the right of $D^b_2$ whenever offpeak usage increases due to the higher peak-period price. As long as these cross-price effects are nonzero, the curves $D^b$ and $D^*$ are distinct from one another.

In going from non-TOD to TOD pricing, we go from the pricing pair $(p, p)$ to $(p_1^*, p_2^*)$ and move from the points $A_1, A_2$ to the points $E_1, E_2$ in peak and offpeak periods, but the welfare measure may be affected by alternative ways of measuring the change. If we first raise the peak-period price from $p$ to $p_1^*$ while holding $p_2$ at the level $p$, then we trace the sequence of points $A_1, C_1, E_1$, yielding a welfare measure given by the area $A_1 C_1 P_1^* P_1$. If instead, price in the offpeak period is first lowered to $P_2^*$, then we trace out the sequence of points in the peak period $A_1, B_1, E_1$, which yields a smaller welfare change represented by the area $A_1 C_1 E_1 B_1$. The corresponding alternative sequence of points in the offpeak period is either $A_2, C_2, E_2$ or $A_2, B_2, E_2$. The welfare changes associated with the sequence of points $ACE$ yield large welfare changes in both peak and offpeak periods, while the changes associated with points $ABE$ yield smaller losses in
Fig. 5.2—Illustration of alternative paths for price changes in two periods of time
peak and smaller gains in offpeak. The sum of the two alternative
measures is unaffected only when the cross-price effects are identical.\footnote{That is, \( \delta q_i / \delta p_j = \delta q_j / \delta p_i \) for quantities \( q \) and prices \( p \) in periods \( i \) and \( j \) of the day.}
Under these circumstances, the welfare measure is said to be path
independent. Otherwise the welfare measure is said to be path de-
pendent.

Fortunately, there is a good measurement approach in applied wel-
fare economics suggested by Turvey (1974). Turvey suggests basing
welfare changes on a linear interpolation between the initial price-
quantity point in each time period, point \( A \) in Fig. 5.2, and the equilib-
rium price quantity point, \( E \). The interpolation is shown as \( D_i \)
in Fig. 5.2. When the condition of path independence is satisfied, the Turvey
approximation yields identically the same result as the line integral
over the demand curves,\footnote{In our application, we take a linear interpolation between points \( A \) and \( E \), which differs slightly from the line integral if there is some curvature between these points. Given the magnitudes involved, this approximation difference is negligible.} and when path independence is not satisfied, it
represents a middle ground between alternative paths for which there
is no a priori basis for selecting one path over another. In other words,
the Turvey approximation, which is convenient to use because it
requires knowing only the initial and final pairs of prices and quan-
tities, is a very robust measure of welfare effects.

The linear interpolation in the Turvey approximation yields a wel-
fare change given by the equation

\[
\Delta W = -1/2 \sum_{i=1}^{n} \Delta p_i \Delta q_i
\]

where \( \Delta W \) is change in welfare, \( \Delta p_i \) is change in the price of good \( i \),
and \( \Delta q_i \) is change in the quantity of good \( i \), for a total of \( n \) goods.\footnote{Changes are defined as new amount minus old amount for prices, quantities, and welfare.} In
electricity analysis, electricity consumption in each rating period is
considered as a separate good.

This scheme permits formal quantitative analysis of welfare gains.
We take change in relative peak load as derived empirically from the
ten-utility data base and derive mean change in quantity at mean lev-
els of usage for the relevant group. For purposes of illustration, we use
energy and demand prices in each rating period that are set at average
levels observed across all firms in the ten-utility database. Since we
measure total change in use in a given period of time, we are incor-
porating both own- and cross-price effects into our measure. The
reference price, \( p \), for a non-time-differentiated electricity rate is
defined as a single price that raises the same total revenue as the
time-of-day rate structure under the assumption of no change in total
consumption. All price levels are stated in constant 1983 dollars.

WELFARE ASSESSMENT OF TOD RATES FOR THE
LARGE CUSTOMERS AS A GROUP

In the ten utilities we studied, TOD rates have been applied on a
mandatory basis to all commercial and industrial customers down to
some size cutoff. We first ask the question: Did this pricing policy
increase welfare? That is, did the total benefits of TOD prices for
these customers exceed the metering costs? The results of the calcula-
tions are shown in Table 5.1. In making this calculation, we use an
illustrative TOD rate which has weighted average values of tariff
characteristics across our ten utilities; as always, the weights are
initial-year average hourly kwh. This illustrative rate is shown in

Table 5.1

WELFARE GAINS USING AVERAGE VALUES OF TOD RATES
FOR THE LARGE CUSTOMER CLASS AS A WHOLE

<table>
<thead>
<tr>
<th>Item</th>
<th>Peak</th>
<th>Shoulder/Offpeak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tariff (approximate average values)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hours (Monday-Friday)</td>
<td>8.4</td>
<td>15.6</td>
</tr>
<tr>
<td>$/kwh</td>
<td>0.059</td>
<td>0.031</td>
</tr>
<tr>
<td>$/kwh</td>
<td>5.50</td>
<td>0.36</td>
</tr>
<tr>
<td>Equivalent price</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOD, $/kwh</td>
<td>0.100</td>
<td>0.046</td>
</tr>
<tr>
<td>Flat, $/kwh</td>
<td>0.067</td>
<td>0.067</td>
</tr>
<tr>
<td>Change in relative load (%)</td>
<td>-0.97</td>
<td>0.46</td>
</tr>
<tr>
<td>Average kwh consumption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Monday-Friday)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hourly</td>
<td>1932</td>
<td>984,326</td>
</tr>
<tr>
<td>Monthly</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in peak period kwh</td>
<td>-5470</td>
<td></td>
</tr>
<tr>
<td>Change in welfare</td>
<td></td>
<td>$82</td>
</tr>
</tbody>
</table>
The effective price per kwh in each rating period is the average revenue per kwh for each customer in that period of time (including the demand charge per customer multiplied by that customer’s maximum demand) averaged over all customers. We state this tariff as a simple two-period tariff with a peak period of approximately eight hours per day and a combined shoulder/offpeak period of about 16 hours.

The reference price, \( p \), against which welfare calculations are made, is based on the average revenue per kwh from the class as a whole. The effective price per kwh for all customers is $0.100 versus $0.067 per kwh in peak—a 46 percent increase, and $0.046 versus $0.067 in shoulder/offpeak, a 31 percent decrease. As presented above, overall, this group of customers reduced its relative peak usage by 0.97 percent. At mean levels of consumption, this reduction provides a 3340 kwh drop in peak period consumption per month. We assume no change in total electricity use, so there is a corresponding increase in offpeak consumption. The welfare gain of this adjustment is $82 per customer per month overall, or about $1000 per year.

The costs of TOD rates are primarily incremental metering costs to measure energy and maximum demand in peak and offpeak periods. In many instances, suitable metering equipment was already in place for these large customers before TOD rates were introduced, so incremental metering costs were zero. Where meters need to be purchased, suitable models are available at a cost of $350 to $600 installed in 1983. Using high values for interest and amortization to calculate annual costs, these meters have an annual carrying cost of less than $65. Consequently, the TOD rates produce an annual welfare gain of $1000 against a metering cost of $65, for a net gain of over $900 per customer on average.

This is a conservative estimate of gain over the long run for a number of reasons. First, it is based on the first year response to TOD rates; common sense suggests that firms continuing on TOD rates will make additional reductions in relative peak load in the long run. Some firms may make more fundamental changes in their time-of-day

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6All prices are inflated to 1983 dollars using a value of 215 for the implicit GNP deflator.
7In some utility systems, there might be incremental analytic costs to determine appropriate TOD prices and rating periods. In the case of the ten utilities studied, their PUC's ordered that TOD rate alternatives be presented along with non-TOD rates, so these analytic costs were sunk before the rates were adopted.
8See Acton (1982) for meter costs.
9This calculation assumes a cost of $600 per meter, 15-year service life, and an 8 percent real discount rate.
consumption patterns as TOD rates are a permanent feature. This could be due to capital investments designed to take advantage of TOD rates—such as greater capacity for offpeak production, greater storage capacity for intermediate products produced in offpeak, more efficient equipment for uses in peak periods, production control equipment to optimize consumption under a more complex rate, and so forth. It could also be due to learning by doing on management's part, including the effects of having a set of managers who "grew up" with TOD rates. Second, these welfare measures are calculated for consumption Monday through Friday. Since only shoulder and offpeak rates apply weekends, additional welfare gains are achieved during those periods, increasing the net benefit.

SHOULD TOD RATES BE EXTENDED TO ALL LARGE BUSINESS CUSTOMERS IN OTHER STATES?

The analysis in the previous subsection suggests that the answer is yes. TOD rates for large business customers have clearly increased economic welfare in the states where they are now in place; extending them to cover similar customers in other states should produce similar increases in welfare. On the other hand, the analysis in Sec. III suggests consideration of an alternative policy: targeting TOD rates so that they apply only to responsive customers. We found in Sec. III that most business customers have not responded to TOD rates so far. Only 4 percent of industrial customers appear to have changed their consumption patterns, and commercial customers have not responded at all. In principle, TOD rates that applied only to responsive customers would be even more efficient than such rates applied to all large customers. Targeted rates would achieve all of the potential increase in consumer and producer surplus, while avoiding the costs of TOD meters for the large majority of firms that do not respond. However, targeting TOD rates so that they apply only to responsive customers may not be a good policy for several reasons.

10See Acton, Gelbard, Hosek, and McKay (1980) for a discussion of some capital investments observed in British firms ten or more years after TOD rates were introduced.

11In this context, "similar" customers are businesses like those included in our data base. Although primarily the very largest electricity consumers in their areas, they include a few medium sized firms with average hourly electricity consumption as low as 100 kwh. However, most are much larger, with an overall average of nearly 2000 kwh per hour. The related issue of whether TOD rates should be extended to smaller business customers is discussed below.
First, in practice, precise targeting of individual responsive customers would be difficult or impossible. We know little about what makes some firms respond and others not respond. In fact, there is some evidence that firms themselves are not very good at predicting their own response to TOD rates before actually facing such rates. While we were acquiring this data set, some utility representatives told us of individual customers who testified at the time TOD rates were first considered that they could not respond at all and that the rates would be punitive. Some of these firms turned around and made dramatic adjustments in their consumption patterns, leading in one case to an overall saving of close to $500,000 per year.

As a practical matter, the most that could be done is to target groups of firms that contain larger than average proportions of responsive firms. Thus, for example, TOD rates might be applied only to industrial and not commercial customers. Alternatively, they might be applied only to certain responsive industrial groups, such as primary metals manufacturers.

Second, group targeting, even when technically feasible, may not be good policy in the long run. Firms may make adjustments to their consumption patterns in the long run, even if they fail to respond in the first year under TOD rates. The installation of computerized load management systems can change commercial customers from unresponsive customers into responsive ones. If commercial customers are exempted from TOD rates, their incentives to install such systems are reduced, and the long-run decrease in peak load will also be reduced. Other firms might show greater response in the long run as they experiment with changes in their production processes, install greater capacity for offpeak consumption, or develop a middle management structure composed of individuals who "grew up" with TOD rates. If they were excluded from targeted TOD rates, such firms might never begin this process of long-term adjustment.

Even a small chance that initially unresponsive firms will respond in the long run justifies applying TOD rates to all large business customers, including both industrial and commercial customers. A typical responsive customer in this large customer class creates welfare gains on the order of $36,000 per year. The expected value of such a big

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12 We have few data on the characteristics of individual firms, and the terms of our agreement with the utilities prohibited us from contacting their customers.

13 Table 5.1 calculates welfare gains for the average customer of $82 per month based on a 0.97 percentage point reduction in relative peak load. The average responsive customer reduces relative peak load by 36 percentage points (Table 3.6), and thus produces a welfare gain of (36/.97) x 82 = $5000 per month or $60,000 per year.
welfare gain exceeds the annual metering cost of $65 even if the probability of long-run response is well under 1 percent.

Third, besides considerations of feasibility and long-run efficiency, evenhandedness in ratemaking may lead the ratemaker to apply identical TOD rates to all customers served at a given voltage level or to all customers whose electricity use exceeds some particular value, regardless of whether or not those customers are expected to change their consumption patterns in any measurable way. In all U.S. jurisdictions that we reviewed, when mandatory TOD rates were introduced, the regulatory commissions found that the rates should apply equally within a voltage or size-of-use category. Since it is not simple to create an objective rationale for discrimination within these categories, we expect that other regulators will also elect to follow a policy of evenhandedness.

SHOULD TOD RATES BE EXTENDED TO SMALLER BUSINESS CUSTOMERS?

The average customer now covered by TOD rates is quite large. Although there are a few relatively small customers in our sample, it is mostly a sample of the very largest firms that were put on TOD rates first. The discussion above deals with the question of whether additional states should adopt TOD rates for similar very large customers. Here we turn to the related question of whether it would be efficient to extend TOD rates to smaller firms than those now covered.

The answer to this question depends on how responsive smaller customers will be. We have no direct evidence on small customer response, since our data are primarily for larger customers. However, we can calculate the appropriate size cutoff for TOD rates on the assumption that small firms react on average in the same way large firms do. Taking average response and relative loads to be as shown in Table 5.1, we ask how small monthly consumption can be and still produce a welfare gain in excess of metering costs. It turns out that for monthly consumption exceeding 15,000 kwh—only 30 kwh per hour on average Monday through Friday—benefits exceed metering costs. Thus we conclude that TOD rates should be extended to smaller business customers. On efficiency grounds, TOD rates can be extended to business customers with quite small levels of electricity consumption.

14The regression results in Sec. IV indicate that small firms respond somewhat less than larger firms do, but because the estimated difference is small compared to other uncertainties, we ignore it here.
VI. COMPARISON WITH OTHER STUDIES AND DIRECTIONS FOR FUTURE WORK

The preceding analysis is deliberately exploratory in nature and, we believe, yields fairly robust estimates of the effects of TOD rates and their associated welfare effects. Further work with this data set is warranted by the findings to date. Some guidance for this future work comes from earlier analysis of large customer response to TOD rates.

COMPARISON WITH OTHER STUDIES

Three kinds of other studies are available for comparison: individual utility-specific studies, econometric studies of selected customer groupings, and analyses of industrial and commercial response to TOD rates in Europe.

A number of utility load forecasters and analysts have examined their own utility's experience with time-of-day rates. The results of four of these studies are presented in Table 6.1. Generally speaking, these studies consist of a comparison of mean monthly loads before and after the rates were introduced, or in some cases an analysis of month-to-month shifts as seasonal rate changes take effect. The

<table>
<thead>
<tr>
<th>Utility Studies</th>
<th>Percent Reduction in Class Load</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG&amp;E</td>
<td>Peak Energy -1.3 to -2.0</td>
</tr>
<tr>
<td>SCE</td>
<td>-0.7 to -1.2</td>
</tr>
<tr>
<td>SDG&amp;E</td>
<td>-5 to -6</td>
</tr>
<tr>
<td>WISC P&amp;L</td>
<td>-9.7</td>
</tr>
<tr>
<td></td>
<td>Peak Demand -0.6 to -1.6</td>
</tr>
<tr>
<td></td>
<td>-3.5</td>
</tr>
</tbody>
</table>

The studies compared in the table are found in Pacific Gas and Electric Company (1979), Southern California Edison Company (1979), San Diego Gas and Electric Company (1979), and Miller (1978). Later studies exist for some of the utilities.
results are often disaggregated by SIC codes. Overall, the results found by these individual studies, as well as the summary of utility studies reported by Faruqui, Aigner, and Howard (1981) are roughly consistent with the results reported in the present study. Wisconsin Power and Light estimated a response that is substantially larger than ours, but WPL’s data included a few of their largest firms who were already on TOD rates at the earliest part of the data they provided to us; as a consequence our analysis may be missing some customers whose response is notably above average.

A number of economists have applied highly structured models of demand for energy to the time-of-day pattern of electricity consumption. These include studies by Chung and Aigner (1981), Chung (1978), Hirschberg and Aigner (1982), and Tishler (1982). Each of these studies used data from only one utility and imposed requirements on the estimated coefficients consistent with production theory in order to derive empirical estimates. Chung (1978) studied four large cement firms in PG&E’s service territory using 34 months of data. Chung and Aigner (1981) studied 64 large PG&E customers aggregated into 13 different 4-digit SIC codes using 41 months of data. Hirschberg and Aigner (1982) studied 104 SCE customers in 19 2-digit SIC codes using 60 months, and Tishler (1982) studied three SCE customers over 39 months. Except for Hirschberg and Aigner, these modeling efforts have led to econometric estimates of price related response that are apparently greater than what is implied by our overall mean analysis.

Several factors may contribute to the apparent differences. We use a ten-utility data set, while the other studies use only one utility’s data. Our study also covered a somewhat longer time span. Third, the econometric studies need to impose conditions on the estimation equations which could not be tested with their data. It is possible that those assumptions drive some of the apparent findings. In any case, we think it is a useful area of research to attempt to understand reasons for these apparent differences.

The third major source of comparison with U.S. TOD experience is the European experience, where TOD rates have been applied to electricity for several decades. In the mid-1970s, before any U.S. experience existed, European data provided the only source of empirical evidence to guide U.S. deliberations. In one such study, Rand analysts

\[\text{See Kohler et al. (1988).}\]
asked what would be the reduction in six-hour peak loads if U.S. firms were to assume the load shapes of their counterpart French industry. They concluded that relative peak loads would drop between 14 and 25 percent, depending upon the analytic assumption employed.

Clearly this projection is much larger than the U.S. experience to date for these ten utilities. We lack load data on French firms before TOD rates were introduced, so it is impossible to determine what explains the differences, but we can speculate on some reasons. First, French firms face a greater peak/offpeak price differential than most U.S. firms. Second, French firms face a four-hour peak period and a 12-hour shoulder period, where U.S. firms generally face peak periods of six to 14 hours in length. Third, French firms may have had initial load patterns which were already flatter than their U.S. counterpart industries, so that they actually made less of a reduction than might otherwise appear to be the case. Fourth, the French rates had been in effect for as much as two decades when we observed these load shapes. It is possible that many firms display a notably greater load response over a period of several years than are revealed in the first few years on a TOD rate.

A more recent Rand study by Acton and McKay (1983) provides some added evidence that helps to reconcile European and U.S. findings. Using individual firm load data for four days throughout the year, Acton and McKay estimated simple regressions of energy demand in peak, shoulder, and offpeak as a function of prices in each of these periods—as well as a few other explanatory variables. Depending upon the specifications, they found own-price elasticities as follows:

Peak period: $-0.026$ to $-0.043$

Shoulder period: $-0.118$ to $-0.132$

Offpeak period: $-0.614$ to $-0.939$

These own price elasticities during peak period are reasonably close to the elasticities of relative peak load reported in Table 4.4 for U.S. firms, suggesting that there may be some common behavioral response across these firms and that many of the apparent differences are due to differing price levels.

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3See Acton and Mitchell (1981) for a summary of this research.
AREAS FOR FUTURE RESEARCH

Two areas of future research seem especially useful to us. First, we plan to develop applied forecasting tools to assist a load forecaster or rate analyst in applying the results of this research in a particular service territory. Such techniques will permit disaggregation by industry and allow the analyst to estimate the effects of different pricing conditions on expected demands in alternate rating periods.

The second major area of research we think merits attention is to attempt to understand better the reasons for differences between the small overall mean response we observe and the apparently greater price-related response in some of the econometric studies. How many of the differences are due to different numbers of firms, number of utilities, and length of time analyzed? How many of the differences are due to aggregation to two-digit SIC code (as we did) rather than the four-digit SIC code (as other studies sometimes did)? How many are due to assumptions of the econometric models employed? It lies beyond the present study to address these questions but they merit attention.
Appendix A

COMPARISON OF CHANGE IN RELATIVE PEAK LOAD USING DATA FROM JUNE/NOVEMBER AND FEBRUARY/AUGUST

Table A.1
AVERAGE CHANGE IN RELATIVE PEAK LOAD UPON INTRODUCTION OF TOD RATES
(Percentage points)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuing standard rates</td>
<td>0.07 (0.15)</td>
<td></td>
<td>0.12</td>
<td>-0.10</td>
</tr>
<tr>
<td>Introduction of TOD rates</td>
<td>-0.97 (0.13)</td>
<td></td>
<td>-0.72</td>
<td>-1.24</td>
</tr>
<tr>
<td>Continuing TOD rates</td>
<td>-0.12 (0.08)</td>
<td></td>
<td>0.18</td>
<td>0.10</td>
</tr>
</tbody>
</table>

[a] From Table 3.2; estimated as the weighted average of individual firms' changes in relative peak load.
[b] Estimated as the weighted average of individual firms' changes in relative peak load for the months of February and August.
[c] The change in relative peak load for the customer class as a whole, calculated as $(\bar{E}_{kp}/\bar{E}_{kd})_1 - (\bar{E}_{kp}/\bar{E}_{kd})_0$, where $kp$ is average peak hourly kwh, $kd$ is average hourly kwh over the full day, the summations are over all observations in the relevant category, and the subscripts refer to final year (1) and initial year (0).
Table A.2
CHANGE IN RELATIVE PEAK LOAD UPON INTRODUCTION
OF TOD RATES, BY UTILITY
(Percentage points)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>SCE/A81</td>
<td>-1.43 (0.40)</td>
<td></td>
<td>-1.23</td>
<td>-1.37</td>
</tr>
<tr>
<td>SCE/T73</td>
<td>-1.32 (0.39)</td>
<td></td>
<td>-1.03</td>
<td>-1.31</td>
</tr>
<tr>
<td>DWP</td>
<td>-0.17 (0.44)</td>
<td></td>
<td>-0.01</td>
<td>-0.89</td>
</tr>
<tr>
<td>PGE/A23</td>
<td>-1.89 (0.52)</td>
<td></td>
<td>-0.98</td>
<td>-1.87</td>
</tr>
<tr>
<td>PGE/A22</td>
<td>-0.96 (0.41)</td>
<td></td>
<td>-0.09</td>
<td>-1.06</td>
</tr>
<tr>
<td>WEP</td>
<td>-2.40 (0.51)</td>
<td></td>
<td>-1.78</td>
<td>-2.71</td>
</tr>
<tr>
<td>MGE</td>
<td>-1.70 (4.47)</td>
<td></td>
<td>0.29</td>
<td>-1.33</td>
</tr>
<tr>
<td>WPL/CP4</td>
<td>-0.22 (2.07)</td>
<td></td>
<td>0.21</td>
<td>-0.84</td>
</tr>
<tr>
<td>LIL</td>
<td>0.13 (0.74)</td>
<td></td>
<td>-0.26</td>
<td>-0.55</td>
</tr>
<tr>
<td>CON</td>
<td>0.01 (0.36)</td>
<td></td>
<td>-0.37</td>
<td>-0.24</td>
</tr>
</tbody>
</table>

*a From Table 3.3; estimated as the weighted average of individual firms' changes in relative peak load.

*b Estimated as the weighted average of individual firms' changes in relative peak load for the months of February and August.

*c The change in relative peak load for the customer class as a whole, calculated as \((\sum_{kp}/\sum_{kd})_1 - (\sum_{kp}/\sum_{kd})_0\), where kp is average peak hourly kwh, kd is average hourly kwh over the full day, the summations are over all observations in the relevant category, and the subscripts refer to final year (1) and initial year (0).
Table A.3
CHANGE IN RELATIVE PEAK LOAD UPON INTRODUCTION
OF TOD RATES, BY INDUSTRY
(Percentage points)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard Error</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrial nec</td>
<td>-0.54 (0.46)</td>
<td>-0.31</td>
<td>-0.68</td>
</tr>
<tr>
<td>20 Food products</td>
<td>-0.66 (0.64)</td>
<td>-0.15</td>
<td>-0.90</td>
</tr>
<tr>
<td>24 Wood products</td>
<td>-9.06 (1.30)</td>
<td>-4.54</td>
<td>-8.99</td>
</tr>
<tr>
<td>26 Pulp and paper</td>
<td>-0.70 (0.97)</td>
<td>0.93</td>
<td>-0.31</td>
</tr>
<tr>
<td>28 Chemicals</td>
<td>-0.30 (0.67)</td>
<td>-0.33</td>
<td>-0.31</td>
</tr>
<tr>
<td>29 Petroleum</td>
<td>-0.07 (0.50)</td>
<td>0.03</td>
<td>-0.05</td>
</tr>
<tr>
<td>30 Rubber and plastic</td>
<td>-1.94 (1.02)</td>
<td>-1.84</td>
<td>-1.69</td>
</tr>
<tr>
<td>32 Stone, clay, glass</td>
<td>-0.39 (0.69)</td>
<td>-1.66</td>
<td>-0.50</td>
</tr>
<tr>
<td>33 Primary metals</td>
<td>-4.84 (0.68)</td>
<td>-4.01</td>
<td>-4.43</td>
</tr>
<tr>
<td>34 Fabricated metals</td>
<td>-0.53 (0.91)</td>
<td>-0.37</td>
<td>-0.66</td>
</tr>
<tr>
<td>35 Machinery</td>
<td>-6.14 (0.84)</td>
<td>-3.05</td>
<td>-6.39</td>
</tr>
<tr>
<td>36 Electrical machinery</td>
<td>-0.68 (0.66)</td>
<td>-0.35</td>
<td>-0.66</td>
</tr>
<tr>
<td>37 Transportation equip</td>
<td>-0.96 (0.54)</td>
<td>-0.12</td>
<td>-0.89</td>
</tr>
<tr>
<td>48 Communications</td>
<td>0.34 (0.92)</td>
<td>0.27</td>
<td>-0.79</td>
</tr>
<tr>
<td>49 Utilities</td>
<td>-3.03 (1.02)</td>
<td>-3.81</td>
<td>-5.19</td>
</tr>
<tr>
<td>All commercial</td>
<td>-0.03 (0.29)</td>
<td>-0.43</td>
<td>-0.39</td>
</tr>
</tbody>
</table>

---

*From Table 3.4; estimated as the weighted average of individual firms' changes in relative peak load.

*Estimated as the weighted average of individual firms' changes in relative peak load for the months of February and August.

The change in relative peak load for the customer class as a whole, calculated as $(I_{pk}/I_{kd})_1 - (I_{kp}/I_{kd})_0$, where $kp$ is average peak hourly kwh, $kd$ is average hourly kwh over the full day, the summations are over all observations in the relevant category, and the subscripts refer to final year (1) and initial year (0).
Table A.4
ADDITIVE SPECIFICATION OF THE REGRESSION MODEL\(^a\)

<table>
<thead>
<tr>
<th>SIC Code</th>
<th>Coeff.</th>
<th>t-stat.</th>
<th>Variable</th>
<th>Coeff.</th>
<th>t-stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>00</td>
<td>-0.895</td>
<td>(-1.0)</td>
<td>PK</td>
<td>-0.273</td>
<td>(-2.0)</td>
</tr>
<tr>
<td>20</td>
<td>-1.564</td>
<td>(-1.8)</td>
<td>PD</td>
<td>-0.462</td>
<td>(-6.1)</td>
</tr>
<tr>
<td>24</td>
<td>-3.134</td>
<td>(-3.2)</td>
<td>PN</td>
<td>-0.371</td>
<td>(-3.3)</td>
</tr>
<tr>
<td>26</td>
<td>-1.791</td>
<td>(-2.0)</td>
<td>PKHRS</td>
<td>0.0826</td>
<td>(1.4)</td>
</tr>
<tr>
<td>28</td>
<td>-1.277</td>
<td>(-1.4)</td>
<td>SHORT</td>
<td>2.059</td>
<td>(4.4)</td>
</tr>
<tr>
<td>29</td>
<td>-1.292</td>
<td>(-1.4)</td>
<td>SIZE</td>
<td>-0.0166</td>
<td>(-2.0)</td>
</tr>
<tr>
<td>30</td>
<td>-1.318</td>
<td>(-1.4)</td>
<td>SIZE_SQ</td>
<td>-0.0000279</td>
<td>(-0.4)</td>
</tr>
<tr>
<td>32</td>
<td>-1.337</td>
<td>(-1.5)</td>
<td>HEAT</td>
<td>0.0125</td>
<td>(0.2)</td>
</tr>
<tr>
<td>33</td>
<td>-3.397</td>
<td>(-3.8)</td>
<td>COOL</td>
<td>1.0016</td>
<td>(6.6)</td>
</tr>
<tr>
<td>34</td>
<td>-0.215</td>
<td>(-0.2)</td>
<td>NW</td>
<td>1.168</td>
<td>(6.1)</td>
</tr>
<tr>
<td>35</td>
<td>-1.952</td>
<td>(-2.2)</td>
<td>NY</td>
<td>2.440</td>
<td>(6.2)</td>
</tr>
<tr>
<td>36</td>
<td>-1.281</td>
<td>(-1.4)</td>
<td>W77</td>
<td>-1.599</td>
<td>(-3.2)</td>
</tr>
<tr>
<td>37</td>
<td>-1.032</td>
<td>(-1.5)</td>
<td>S78</td>
<td>-1.706</td>
<td>(-4.1)</td>
</tr>
<tr>
<td>48</td>
<td>-0.425</td>
<td>(-0.4)</td>
<td>W78</td>
<td>-1.123</td>
<td>(-2.8)</td>
</tr>
<tr>
<td>49</td>
<td>-2.241</td>
<td>(-2.3)</td>
<td>S79</td>
<td>-1.073</td>
<td>(-2.7)</td>
</tr>
<tr>
<td>50</td>
<td>-1.573</td>
<td>(-1.8)</td>
<td>W79</td>
<td>-0.991</td>
<td>(-2.5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>S80</td>
<td>0.863</td>
<td>(2.3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>W80</td>
<td>-2.429</td>
<td>(-6.3)</td>
</tr>
</tbody>
</table>

\(^a\) Dependent variable is change in relative peak load (percentage points).
Appendix B

LISTING OF COMPUTER CODE FOR
REGRESSION ESTIMATES

ITERATIVE LINEAR ESTIMATION PROGRAM

//P0780R00 JOB (3762,1000,133,20),'TITER',CLASS=V
// EXEC SAS,REGION=1000K,OPTIONS='NONEWS'
//*IN DD DSN=P.P0780.A3767.CHANGE,DISP=(OLD,KEEP),
// * UNIT=HIGH9, VOL=SER=004178, LABEL=150
//IN1 DD DSN=TDI,DISP=(OLD,KEEP),
// UNIT=HIGH9, VOL=SER=006702, LABEL=71
//IN2 DD DSN=ALL,DISP=(OLD,KEEP),
// UNIT=AFF=IN1, VOL=SER=006702, LABEL=72
//******* NOTE: TOD AND ALL ARE MSLABELED (SWITCHED) ON THE TAPE.
// *CHNG DD DSN=P.P0780.A3762.CHANGE,DISP=(NEW,CATLG),
// * UNIT=TEMP, VOL=SER=TEMP11,
// * SPACE=(TRK,(300,300), ELSE)
//ALL DD DSN=P.P0780.A3762.ALL,DISP=(NEW,CATLG),
// UNIT=TEMP, VOL=SER=TEMP11,
// SPACE=(TRK,(300,300),)
//TOD DD DSN=P.P0780.A3762.TOD,DISP=(NEW,CATLG),
// UNIT=TEMP, VOL=SER=TEMP11,
// SPACE=(TRK,(300,300),)
//CDEFF DD DSN=P.P0780.A3762.CDEFF,DISP=(NEW,CATLG),
// UNIT=TEMP, VOL=SER=TEMP11,
// SPACE=(TRK,(20,20),)
//TEMP DD DSN=P.P0780.A3762.TEMP,DISP=(NEW,CATLG),
// UNIT=TEMP, VOL=SER=TEMP11,
// SPACE=(TRK,(300,300),)
//SYSIN DD *

****** CALCULATES NONLINEAR REGRESSIONS OF CHANGE IN RELATIVE
****** PEAK LOAD ON SIC2 AND PRICES, ETC, USING AN ITERATIVE
****** METHOD.
****** THIS RUN IN ON JUN/MAY CHANGE FILE.
****** SAVED AS TITER ON USER33;

OPTIONS GEN=0;

*PROC COPY IN=IN OUT=CHNG;
*RUN;
*OPTIONS OBS=20;
*
*MACRO DROP
* DROP=BLF BLFO BLFP BLFS BREL BRELO BRELS CUSTOMER
* E_EARN E_HRS LF LF0 LFIP LFS RELO RELS SIC TEMP
*
*DATA ALL.CHANGE TOD.CHANGE;
* SET CHNG_SUMMER (IN=S DROOP) CHNG_WINTER (IN=W DROOP);
* IF TOD=1 & CATEGORY=61 THEN DELETE;
* 
* SUM=S;
* WIN=W;
* C11=(CATEGORY=11);
* C12=(CATEGORY=12);
* C21=(CATEGORY=21);
* C31=(CATEGORY=31);
* C41=(CATEGORY=41);
* C51=(CATEGORY=51);
* C61=(CATEGORY=61);
* C71=(CATEGORY=71);
* C81=(CATEGORY=81);
* C82=(CATEGORY=82);
* C83=(CATEGORY=83);
* C91=(CATEGORY=91);
* C92=(CATEGORY=92);
* C101=(CATEGORY=101);
* S00=(SIC2=0);
* S20=(SIC2=20);
* S24=(SIC2=24);
* S26=(SIC2=26);
* S28=(SIC2=28);
* S29=(SIC2=29);
* S30=(SIC2=30);
* S32=(SIC2=32);
* S33=(SIC2=33);
* S34=(SIC2=34);
* S35=(SIC2=35);
* S36=(SIC2=36);
* S37=(SIC2=37);
* S48=(SIC2=48);
* S49=(SIC2=49);
* S50=(SIC2=50);
* SEQ3=(SEQUENCE=3);
* SEQ4=(SEQUENCE=4);
* SEQ5=(SEQUENCE=5);
* SEQ6=(SEQUENCE=6);
* SEQ7=(SEQUENCE=7);
* SEQ8=(SEQUENCE=8);
* SEQ9=(SEQUENCE=9);
* SEQ10=(SEQUENCE=10);
* YR77=(SEQ3 | SEQ4);
* YR78=(SEQ5 | SEQ6);
* YR79=(SEQ7 | SEQ8);
* YR80=(SEQ9 | SEQ10);
* SMALL=(BK28<1000);
* MEDIUM=(1000<=BK28<2000);
* LARGE=(2000<=BK28);
* IF UTILID=1 & SUM=1 THEN PHRHS=6;
* ELSE IF UTILID=1 & WIN=1 THEN PHRHS=5;
* ELSE IF UTILID=2 THEN PKHRS=12;
* ELSE IF UTILID=3 THEN PKHRS=8;
* ELSE IF UTILID=4 THEN PKHRS=13;
* ELSE IF UTILID=5 THEN PKHRS=11;
* ELSE IF UTILID=6 & SUM=1 THEN PKHRS=7;
* ELSE IF UTILID=6 & WIN=1 THEN PKHRS=4;
* ELSE IF UTILID=7 & SUM=1 THEN PKHRS=12;
* ELSE IF UTILID=7 & WIN=1 THEN PKHRS=17;
* ELSE IF UTILID=8 & SUM=1 THEN PKHRS=6;
* ELSE IF UTILID=8 & WIN=1 THEN PKHRS=4;
* ELSE IF UTILID=9 THEN PKHRS=14;
* ELSE IF UTILID=10 THEN PKHRS=14;
* CA=(UTILID=1 | UTILID=3 | UTILID=8);
* MW=(UTILID=2 | UTILID=4 | UTILID=5 | UTILID=6 | UTILID=9);
* NY=(UTILID=7 | UTILID=10);
* SHORT=(PKHRS=8);
* ONE=1;
* WT=8K28/1000;
* SIZE=WT;
* SIZE2=SIZE*SIZE;
* LENGTH SUM WIN C11--C101 S00--S50 SEQ3--SEQ10 YR77--YR80
* SMALL MEDIUM LARGE CA MW NY SHORT ONE 2;

* IF TOD=1 THEN OUTPUT TOD.CHANGE;
* OUTPUT ALL.CHANGE;

PROC COPY IN=IN1 OUT=ALL;
PROC COPY IN=IN2 OUT=TOD;

DATA TOD.CHANGE;
  SET TOD.CHANGE;
  TS00=S00-.398306*S50;
  TS20=S20-.202304*S50;
  TS24=S24-.049382*S50;
  TS26=S26-.089595*S50;
  TS28=S28-.184536*S50;
  TS29=S29-.331466*S50;
  TS30=S30-.080279*S50;
  TS32=S32-.176850*S50;
  TS33=S33-.180976*S50;
  TS34=S34-.100820*S50;
  TS35=S35-.117617*S50;
  TS36=S36-.192668*S50;
  TS37=S37-.290886*S50;
  TS48=S48-.099551*S50;
  TS49=S49-.080438*S50;
  TREL=REL+.0346735*S50;

PROC SYSSREG DATA=TOD.CHANGE OUEST=COEFF.BSIC;
  WEIGHT WT;
  MODEL TREL=TS00--TS49 / NOST COVB;
DATA ALL.CHANGE;
SET ALL.CHANGE;
TS00=S00-.398306*S50;
TS20=S20-.202304*S50;
TS24=S24-.049382*S50;
TS26=S26-.089595*S50;
TS28=S28-.184536*S50;
TS29=S29-.331466*S50;
TS30=S30-.080279*S50;
TS32=S32-.176850*S50;
TS33=S33-.180976*S50;
TS34=S34-.100820*S50;
TS35=S35-.117617*S50;
TS36=S36-.192668*S50;
TS37=S37-.290886*S50;
TS48=S48-.099551*S50;
TS49=S49-.080438*S50;
KEY=1;

MACRO REGX

DATA COEFF.BSIC;
SET COEFF.BSIC (RENAME=(TS00=B00 TS20=B20 TS24=B24 TS26=B26
TS28=B28 TS29=B29 TS30=B30 TS32=B32 TS33=B33 TS34=B34 TS35=B35
TS36=B36 TS37=B37 TS48=B48 TS49=B49));
IF _N_=1;
B50=-(.398306*B00+.202304*B20+.049382*B24+.089595*B26
+.184536*B28+.331466*B29+.080279*B30+.176850*B32
+.180976*B33+.100820*B34+.117617*B35+.192668*B36
+.290886*B37+.099551*B48+.080438*B49+.0346735);
KEY=1;

PROC PRINT DATA=COEFF.BSIC;

DATA TEMP.ALL;
MERGE ALL.CHANGE COEFF.BSIC;
BY KEY;
ARRAY S S00--S50;
ARRAY B B00--B49 B50;
MULT=0;
DO OVER S;
  MULT=MULT+B*S;
END;
ARRAY X XLIST;
DO OVER X;
  X=MULT*X;
END;

PROC SYSREG DATA=TEMP.ALL OUTEST=COEFF.BX;
WEIGHT WT;
MODEL REL=XLIST / NOINT COVB;
MACRO REGSIC

DATA COEFF.BX (DROP=XLIST);
SET COEFF.BX;
IF _N_=1;
ARRAY X XLIST;
ARRAY B BLIST;
DO OVER X;
  B=X;
END;
KEY=1;

DATA TEMP.ALL;
MERGE ALL.CHANGE COEFF.BX;
BY KEY;
ARRAY X XLIST;
ARRAY B BLIST;
MULT=0;
DO OVER X;
  MULT=MULT+B*X;
END;
ARRAY TS TS00--TS49;
DO OVER TS;
  TS=MULT*TS;
END;
TREL=REL+MULT*.0346735*S50;

PROC SYSSREG DATA=TEMP.ALL OUTFEST=COEFF.BSIC;
WEIGHT WT;
MODEL TREL=TS00--TS49 / NOSTD COVB;

MACRO XLIST ONE PK PD PN PKHRS SHORT SIZE SIZE2 %
MACRO BLIST BONE BPK BPD BPN BPKHRS BSHORT BSIZE BSIZE2 %

REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
REGX REGSIC
FULL NONLINEAR ESTIMATION PROGRAM

//PO780000 JOB (3762,2000,133,20),'NONLIN',CLASS=V
// EXEC SAS,REGION=1000K,OPTIONS='NONEWS'
// IN DD DSN=TOD,DISP=(OLD,KEEP),
// * UNIT=HIGH9, VOL=SER=006702, LABEL=71
// *** WARNING: LABEL ON TAPE IS REUSL' NOT 'TOD'
// ALL DD DSN=T.P0760.A3762,ALL,DISP=SJR,
// UNIT=TEMP, VOL=SER=TEMP11,
// SPACE=(TRK,(300,300),)
// SYSIN DD *

******* CALCULATES NONLINEAR REGRESSIONS OF CHANGE IN
******* RELATIVE PEAK LOAD ON SIC2 AND OTHER VARIABLES.
******* THIS RUN IN ON JUN/NOV CHANGE FILE.
******* IDENTIFYING CONSTRAINT IMPOSED ON SIC COEFFICIENTS;
******* SAVED AS NONLIN ON USER59;

OPTIONS GEN=0;

*PROC COPY IN=IN OUT=ALL;
*RUN;
*OPTIONS OBS=200;

PROC NLIN DATA=ALL CHANGE METHOD=MARQUARDT CONVERGENCE=.000001
ITER=16;
PARAMETERS
   BONE=.269333 BPK=.321145 BPD=.315725
   BPN=.191781 BPKHRS=.167280 BSHOR=.1.55044 BSIZ=.019682
   BSIZE=.0011657
   B20=.0057759 B20=.011906 B24=.140568 B26=.00571096
   B28=.00123356 B29=.00045047 B30=.026539 B32=.00862836
   B33=.059067 B34=.0079054 B35=.033074 B36=.010268
   B37=.00877492 B48=.001168262 B49=.00710250
S00=S00-.398306*S50;
S20=S20-.20304*S50;
S24=S24-.049382*S50;
S26=S26-.089595*S50;
S28=S28-.184536*S50;
S29=S29-.331466*S50;
S30=S30-.080279*S50;
S32=S32-.176850*S50;
S33=S33-.180767*S50;
S34=S34-.100820*S50;
S35=S35-.117617*S50;
S36=S36-.192668*S50;
S37=S37-.290886*S50;
S48=S48-.095551*S50;
S49=S49-.080438*S50;
X = BONE*ONE + BPK*PK + BPD*PD + BPN*PN + BPKHRS*PKHRS
   + BSHOR*SHOR + BSIZE*SIZE + BSIZE2*SIZE;
S = B00*S00 + B20*S20 + B24*S24 + B26*S26 + B28*S28 + B29*S29
   + B30*S30 + B32*S32 + B34*S34 + B35*S35 + B36*S36 + B37*S37 + B38*S38
   + B39*S39 + B40*S40 + B41*S41 + B42*S42 + B43*S43 + B44*S44
   + B45*S45 + B46*S46 + B47*S47 + B48*S48 + B49*S49;

X = BONE*ONE + BPK*PK + BPD*PD + BPN*PN + BPKHRS*PKHRS
   + BSHOR*SHOR + BSIZE*SIZE + BSIZE2*SIZE;
S = B00*S00 + B20*S20 + B24*S24 + B26*S26 + B28*S28 + B29*S29
   + B30*S30 + B32*S32 + B34*S34 + B35*S35 + B36*S36 + B37*S37 + B38*S38
   + B39*S39 + B40*S40 + B41*S41 + B42*S42 + B43*S43 + B44*S44
   + B45*S45 + B46*S46 + B47*S47 + B48*S48 + B49*S49;

X = BONE*ONE + BPK*PK + BPD*PD + BPN*PN + BPKHRS*PKHRS
   + BSHOR*SHOR + BSIZE*SIZE + BSIZE2*SIZE;
S = B00*S00 + B20*S20 + B24*S24 + B26*S26 + B28*S28 + B29*S29
   + B30*S30 + B32*S32 + B34*S34 + B35*S35 + B36*S36 + B37*S37 + B38*S38
   + B39*S39 + B40*S40 + B41*S41 + B42*S42 + B43*S43 + B44*S44
   + B45*S45 + B46*S46 + B47*S47 + B48*S48 + B49*S49;
+ B30*S30 + B32*S32 + B33*S33 + B34*S34 + B35*S35 + B36*S36
+ B37*S37 + B48*S48 + B49*S49 - .0346735*S50;
DER.BONE=ONE*S;
DER.BFR=FK*S;
DER.BPD=PD*S;
DER.BPN=PN*S;
DER.BPKHRS=PKHRS*S;
DER.BSHORT=SHORT*S;
DER.BSIZE=SIZE*S;
DER.BSIZE2=SIZE2*S;
DER.B00=S00*X;
DER.B20=S20*X;
DER.B24=S24*X;
DER.B26=S26*X;
DER.B28=S28*X;
DER.B29=S29*X;
DER.B30=S30*X;
DER.B32=S32*X;
DER.B33=S33*X;
DER.B34=S34*X;
DER.B35=S35*X;
DER.B36=S36*X;
DER.B37=S37*X;
DER.B48=S48*X;
DER.B49=S49*X;
_WEIGHT_ = WT;
MODEL REI=X*S;
BIBLIOGRAPHY


